Unsing Convolutional Neural Networks For Segmentation Of Multiple Sclerosis Lesions In 3d Mri

A Research Project

Abstract

Multiple Sclerosis (MS) is a chronic neurological disorder that affects the central nervous system and is characterized by the formation of lesions in the brain and spinal cord. Accurate segmentation of these lesions from Magnetic Resonance Imaging (MRI) scans is essential for early diagnosis, disease monitoring, and treatment planning. However, manual lesion segmentation is time-consuming, labor-intensive, and subject to variations among radiologists. This study developed a 3D U-Net deep learning model for the automated segmentation of Multiple Sclerosis lesions using three-dimensional brain MRI images. The study utilized the Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information, obtained from Kaggle and originally published on Mendeley Data. The dataset consists of MRI scans from 60 patients, including T1-weighted, T2-weighted, and FLAIR images with expert-annotated lesion segmentation masks. The FLAIR MRI images and their corresponding lesion masks were selected for this study because they provide enhanced visualization of MS lesions. The MRI volumes were preprocessed through data cleaning, normalization, resizing to 128 × 128 × 64 voxels, binary mask generation, and dataset partitioning before model training.

The proposed 3D U-Net model was implemented using Python, TensorFlow, and Keras in the Google Colaboratory environment. Three dataset partitioning strategies (65:35, 70:30, and 80:20) were evaluated to determine the effect of different training and testing data distributions on model performance. The model was trained using the Adam optimizer with a combination of Dice Loss and Binary Cross-Entropy loss functions. Performance evaluation was carried out using Accuracy, Precision, Recall, Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and Precision–Recall Curve. The experimental results showed that the 70:30 partition achieved the highest segmentation accuracy of 97%, while the 65:35 and 80:20 partitioning strategies each achieved 95% accuracy. These findings demonstrate that the proposed 3D U-Net model is effective for automated Multiple Sclerosis lesion segmentation and has the potential to support clinicians in improving the accuracy and efficiency of MRI-based diagnosis and disease monitoring.

Keywords: Multiple Sclerosis, 3D U-Net, Deep Learning, MRI, Lesion Segmentation, Medical Image Analysis, Convolutional Neural Network (CNN).

CHAPTER ONE

INTRODUCTION

1.0 Background of the Study

Gudbergsen et al., (2013) Multiple Sclerosis (MS) is a chronic autoimmune disease that primarily affects the central nervous system (CNS), including the brain, spinal cord, and optic nerves. It is characterized by the demyelination of axons, neuroinflammation, and neuronal loss, which disrupt the normal transmission of electrical signals along nerve fibers. The consequences of these pathological changes manifest clinically as a wide spectrum of neurological symptoms, ranging from motor impairments such as muscle weakness, spasticity, and tremors, to sensory disturbances including numbness and tingling, to cognitive dysfunction such as impaired memory and attention, as well as visual disturbances and fatigue. The heterogeneity in symptom presentation makes early diagnosis particularly challenging, as the disease may mimic other neurological disorders. Early and accurate detection of MS lesions is therefore essential to initiate timely therapeutic interventions, slow disease progression, reduce long-term disability, and improve the quality of life of patients (Filippi et al., 2018).

Miller et al., (2012) The prevalence of MS has been increasing globally, with over 2.8 million people affected worldwide. The disease exhibits higher prevalence in women than men, and the onset typically occurs between ages 20 and 40. The variable course of the disease, which may be relapsing-remitting, secondary progressive, or primary progressive, requires continuous monitoring of disease activity through imaging and clinical assessment. MRI has become the cornerstone of MS diagnosis and disease monitoring, providing non-invasive, high-resolution images of both white and gray matter lesions. Lesion assessment enables clinicians to track disease progression, evaluate treatment response, and predict long-term outcomes. However, despite its sensitivity, MRI interpretation is labor-intensive and highly dependent on the expertise of radiologists, making automated approaches highly desirable (Bakshi et al., 2005).

Shiee et al., (2010) MRI sequences used in MS evaluation include T1-weighted, T2-weighted, and FLAIR images. T1-weighted sequences are particularly useful in identifying chronic lesions and areas of tissue loss, while T2-weighted sequences capture active inflammation and edema. FLAIR sequences enhance lesion visibility by suppressing cerebrospinal fluid (CSF) signals, providing better contrast for periventricular and cortical lesions. Despite the diagnostic utility of these sequences, manual lesion segmentation is prone to inter-observer variability,

subjective errors, and limited reproducibility, particularly when dealing with small or diffuse lesions. This makes the need for automated and standardized approaches to lesion detection and volumetric quantification critical for clinical practice and research (John et al., 2022).

LeCun et al., (2015) Advances in artificial intelligence and deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized medical image analysis. CNNs automatically extract hierarchical features from imaging data, capturing low-level features such as edges and textures, mid-level patterns like shapes and lesion morphology, and high-level contextual information including spatial distribution of lesions. This hierarchical learning enables CNNs to identify subtle abnormalities that may be missed during manual inspection. In the context of MS, CNNs provide automated, accurate, and reproducible segmentation of lesions, which is critical for disease tracking, clinical trials, and personalized therapy planning.

Hashemi et al., (2023) Recent studies have explored various CNN architectures for MS lesion segmentation. 3D CNNs have become increasingly popular because they can leverage volumetric data from MRI scans, capturing inter-slice relationships that are lost in 2D models. The 3D U-Net architecture, along with variants such as VGG-UNet and GAU U-Net, has shown significant improvements in detecting small and irregularly shaped lesions due to their encoder-decoder structures and skip connections, which preserve spatial information while aggregating multi-scale contextual features. Multi-modal networks that combine FLAIR, T1, and T2 sequences further improve performance by leveraging complementary information from different MRI modalities. Attention mechanisms integrated into CNNs allow the network to focus selectively on lesion areas, improving sensitivity and reducing false positives (Roy et al., 2023).

John et al., (2022) Despite these technological advances, several challenges remain. MS lesions vary greatly in size, shape, intensity, and location, which makes detection of small, subtle, or newly forming lesions particularly difficult. Variations in MRI acquisition protocols, scanner types, and patient populations introduce domain shifts, reducing the generalizability of CNN models across different clinical centers. Furthermore, most CNN models operate as black boxes, producing segmentations without interpretable explanations. Clinicians require models that not only segment lesions accurately but also provide confidence estimates or visual explanations to support clinical decision-making. Addressing these challenges is crucial for developing CNN-based systems that are reliable, generalizable, and clinically acceptable (Ghafoorian et al., 2017).

Roy et al., (2023) Another critical consideration is the need for volumetric quantification of lesions, which provides objective metrics for disease progression and treatment response. Automated CNN-based frameworks enable rapid and consistent assessment of lesion volume, lesion count, and spatial distribution, which are essential for longitudinal studies and personalized treatment plans. Moreover, integrating multi-modal data and attention mechanisms can further enhance detection performance, particularly for subtle lesions that are often overlooked in conventional manual analysis. These capabilities demonstrate the transformative potential of CNN-based 3D MRI analysis for MS, offering the prospect of faster, more accurate, and reproducible assessment of disease burden.

Zhang et al., (2023) In conclusion, the combination of high-resolution 3D MRI data and advanced CNN architectures provides a powerful approach to address the limitations of manual lesion segmentation. Developing robust, interpretable, multi-modal 3D CNN frameworks is essential not only to improve lesion detection and volumetric quantification but also to facilitate early diagnosis, monitor disease progression, guide therapy, and ultimately enhance patient outcomes. This growing intersection of medical imaging and deep learning represents a crucial advancement in the management of Multiple Sclerosis.

1.1 Statement of the Problem

Raab et al., (2023) Although deep learning has greatly advanced automated analysis of medical images, accurate segmentation of Multiple Sclerosis (MS) lesions in 3D MRI remains a critical challenge in both research and clinical practice. MS lesions vary considerably in size, shape, intensity, and anatomical location, with some lesions appearing very small or subtle and others showing irregular morphology. These small and subtle lesions are particularly important in early disease detection and monitoring progression, yet even advanced convolutional neural networks (CNNs) often fail to detect them reliably because of limited contrast, heterogeneous appearance, and the presence of noise in MRI scans. These missed detections can lead to underestimation of disease burden, delayed treatment adjustments, and potentially poorer patient outcomes, underscoring a significant gap in current segmentation methodologies.

Seehafer et al., (2024) A significant barrier to developing robust CNN models for MS lesion segmentation is variability in input data from different MRI protocols and scanners. Research comparing 2D- and 3D-FLAIR datasets, it shows that 3D sequences tend to detect more

small lesions than 2D sequences, but differences in slice thickness, contrast weighting, and scanner settings often lead to inconsistent lesion counts and volumetric measures across datasets, even when using automated processing pipelines such as deep learning-based tools. These inconsistencies make it difficult for models trained on one dataset to generalize to others, especially in multi-center clinical environments where diversity in imaging protocols is the norm rather than the exception.

Greselin et al., (2024) Another major problem is class imbalance within MRI datasets. MS lesions occupy only a small fraction of the brain volume, whereas the majority of voxels represent healthy tissue. CNNs trained on such imbalanced data tend to favor prediction of healthy tissue, which leads to high false negatives and an overall reduction in sensitivity, particularly for lesions that are small, contrast-poor, or situated in complex anatomical regions. Moreover, even when networks achieve acceptable overlap metrics (e.g., Dice scores), the underlying predictions may still miss clinically relevant lesion features or fail to reflect lesion progression accurately over time.

Jain et al., (2026) Contemporary approaches such as MS-DASPNet attempt to enhance segmentation performance using dual attention mechanisms and spatial pyramid pooling combined with transfer learning. Although these innovations improve feature discrimination and help capture richer contextual information, major challenges remain in balancing sensitivity and specificity, especially when evaluating on external datasets or clinical scans that differ from training data. Without robust domain adaptation and generalization, these sophisticated networks can still produce unstable or inconsistent outputs when deployed outside controlled research environments.

In light of these challenges, developing robust, multi-modal, and generalizable 3D CNN frameworks that can accurately segment MS lesions across variable MRI inputs, detect small and subtle lesions, address class imbalance, and offer interpretable, clinically actionable outputs remains an unmet need in neuroimaging research. Solving these problems is essential for transitioning CNN-based segmentation from research environments into reliable tools for routine clinical diagnosis, longitudinal monitoring, and personalized treatment planning for MS patients.

1.2 Research Aim and Objectives

The aim of this study is to develop a Convolutional Neural Network-based model for accurate segmentation of Multiple Sclerosis lesions in 3D MRI scans. The Specific objectives are however, include the following:

i. To collect and preprocess MRI datasets suitable for training deep learning models.
ii. To design and implement a CNN-based architecture for automated segmentation of MS lesions in 3D MRI images.
iii. To train and validate the CNN model using annotated MRI datasets.
iv. To evaluate the performance of the proposed model using segmentation metrics such as Dice Similarity Coefficient, accuracy, precision, and recall.

1.3 Significance of the Study

This study is significant for several important reasons, particularly in improving medical image analysis and supporting the diagnosis and management of Multiple Sclerosis.

i. **Improvement in Diagnostic Accuracy:** Accurate identification and segmentation of MS lesions are critical for understanding disease severity and progression. Conventional methods rely on radiologists manually analyzing MRI scans, which can be time-consuming, subjective, and prone to inter- and intra-observer variability. The use of 3D Convolutional Neural Networks (CNNs) enables automated and highly consistent lesion detection, reducing human error while capturing subtle lesions that may be overlooked during manual evaluation. Enhanced diagnostic accuracy supports early disease detection, informs treatment decisions, and allows for precise monitoring of disease activity over time.
ii. **Reduction in Time and Resource Requirements:** Manual MRI analysis is resource-intensive, often requiring hours per patient scan and multiple expert reviewers to ensure accuracy. By applying CNN-based automated segmentation, this study significantly reduces the time and human resources required for MRI evaluation. Faster processing enables radiologists to focus on complex clinical interpretation and reduces bottlenecks in high-volume clinical settings. Additionally, automated methods allow healthcare facilities to handle larger patient cohorts, improving overall efficiency in diagnosis and monitoring.
iii. **Enhancement of Clinical Decision-Making:** The automated system provides quantitative and consistent outputs, such as lesion volume, lesion load, and progression over time. These metrics offer clinicians reliable tools to monitor disease progression, assess treatment

response, and make informed decisions regarding therapy adjustments. Furthermore, the system's ability to provide reproducible and objective measures ensures uniform standards of care across institutions and reduces the subjectivity associated with manual lesion evaluation.

iv. **Support for Personalized Medicine:** This study's contributions extend to personalized patient care, as accurate lesion mapping and quantification allow for tailoring treatment strategies to individual patient needs. Patients with rapidly progressing or highly active lesions can be identified earlier, enabling timely initiation or adjustment of disease-modifying therapies. Personalized monitoring can potentially improve long-term patient outcomes, slow disease progression, and enhance quality of life.

v. **Advancement of Standardized Clinical Protocols:** Automated CNN-based segmentation tools can contribute to standardizing lesion assessment protocols across institutions, ensuring consistent evaluation and reducing inter-hospital variability. Standardization is essential for multicenter studies, clinical trials, and collaborative research, where consistent lesion quantification is critical for comparative analysis.

vi. **Facilitation of Longitudinal Monitoring:** MS is a chronic and progressive disease. The ability of CNN-based systems to track lesion changes over time allows for detailed longitudinal studies, enabling clinicians and researchers to observe disease evolution and the impact of therapies. Automated longitudinal analysis reduces variability in measurements, increases reliability, and enhances our understanding of disease dynamics, which is essential for both clinical practice and research studies.

vii. **Foundation for Future Research and Innovation:** The methodologies developed in this study provide a foundation for future research, including hybrid deep learning models, multi-modal imaging analysis, and explainable AI for medical imaging. Researchers can build upon this work to create models capable of predicting disease progression, integrating patient clinical data, and offering automated prognosis. This study also encourages the development of robust, generalizable algorithms capable of handling heterogeneous datasets from multiple scanners and centers.

1.4 Scope and Limitations of the Study

This study focuses on the development of a CNN-based system for segmenting Multiple Sclerosis lesions from 3D MRI brain images.

i. **Utilization of public MRI datasets for MS patients:** The study employs publicly available and benchmark MRI datasets of Multiple Sclerosis (MS) patients, including FLAIR, T1-weighted, and T2-weighted sequences, to ensure a diverse and representative set of brain lesion patterns. These datasets provide rich multi-modal imaging information that improves lesion visibility and characterization.
ii. **Implementation of 3D CNN architectures:** The study develops and evaluates 3D Convolutional Neural Network (3D-CNN) models for volumetric brain image segmentation. These models are designed to capture spatial relationships across MRI slices, improving lesion detection accuracy compared to traditional 2D approaches.
iii. **Performance evaluation using standardized metrics:** The effectiveness of the proposed model will be assessed using widely accepted segmentation evaluation metrics such as Dice Similarity Coefficient (DSC), Jaccard Index (IoU), sensitivity, specificity, and volumetric accuracy.
iv. **Analysis of lesion distribution and characteristics:** Beyond segmentation, the study also examines the spatial distribution, size, morphology, and volume of MS lesions within the brain. This analysis provides deeper insight into disease severity and progression patterns.

The Limitations of the Study include the following:

i. **Availability and quality of labeled datasets:** A major limitation of this study is the reliance on publicly available MRI datasets, which may have limited size and inconsistent annotation quality. Since manual labeling of MS lesions requires expert radiologists, variations in labeling accuracy may affect the model's training quality and reduce its ability to generalize effectively to unseen clinical data.
ii. **Computational resource requirements:** Training and deploying 3D CNN models on volumetric MRI data is computationally expensive, requiring high-performance GPUs, large memory capacity, and extended processing time. These resource demands may limit experimentation, model optimization, and scalability, especially in low-resource environments or smaller research institutions.
iii. **Variability in MRI scanning protocols:** MRI scans collected from different hospitals and imaging centers often vary in terms of scanner type, magnetic field strength, slice thickness, contrast settings, and image resolution. This heterogeneity introduces domain variability that may reduce the model's performance when applied to external datasets, making generalization across institutions more challenging.

iv. **Difficulty in detecting subtle lesions:** Despite the use of advanced CNN architectures, the detection of very small, low-contrast, or early-stage MS lesions remains challenging. These lesions may be difficult to distinguish from surrounding healthy tissue due to weak intensity differences, noise, or imaging artifacts, potentially leading to under-segmentation in some cases.

v. **Limited clinical integration:** The proposed system is designed as a decision-support tool rather than a fully automated diagnostic system. While it can assist clinicians by providing segmentation results, final diagnosis and treatment decisions still depend on expert medical interpretation, patient history, and additional diagnostic tests.

vi. **Lack of longitudinal disease tracking:** This study primarily focuses on single-scan MRI segmentation and does not fully incorporate long-term tracking of lesion progression across multiple time points. As a result, it does not yet provide complete temporal analysis of disease evolution, which is important for monitoring treatment effectiveness and long-term disease behavior.

1.5 Definition of Terms

i. **Multiple Sclerosis (MS):** Multiple Sclerosis is a chronic, autoimmune neurological disorder in which the immune system attacks the protective covering (myelin sheath) of nerve fibers in the central nervous system. This results in disrupted nerve signal transmission, leading to a wide range of physical, cognitive, and sensory impairments.

ii. **Central Nervous System (CNS):** The Central Nervous System consists of the brain, spinal cord, and optic nerves. It serves as the primary control center of the body, responsible for processing sensory information, coordinating movement, and regulating cognitive functions.

iii. **Demyelination:** Demyelination refers to the damage or loss of the myelin sheath surrounding nerve fibers. This condition impairs the speed and efficiency of electrical signal transmission along neurons, which is a hallmark feature of Multiple Sclerosis.

iv. **Neuroinflammation:** Neuroinflammation is the inflammatory response within the nervous system caused by immune system activity. In MS, it contributes significantly to tissue damage, lesion formation, and disease progression.

v. **Neuronal Loss:** Neuronal loss is the degeneration or death of nerve cells (neurons), resulting in reduced brain functionality. It is associated with long-term disability and cognitive decline in MS patients.

vi. **Magnetic Resonance Imaging (MRI):** Magnetic Resonance Imaging is a non-invasive imaging technique that uses magnetic fields and radiofrequency waves to produce high-resolution images of internal body structures, particularly the brain and spinal cord.

vii. **MRI Lesions:** MRI lesions are abnormal areas detected in brain or spinal cord images that indicate tissue damage, inflammation, or demyelination. In MS, these lesions are key indicators used for diagnosis and disease monitoring.

viii. **T1-Weighted MRI:** T1-weighted MRI is an imaging sequence that provides detailed anatomical information and is particularly useful for identifying chronic lesions, tissue degeneration, and areas of permanent damage in MS patients.

ix. **T2-Weighted MRI:** T2-weighted MRI is an imaging sequence that highlights fluid and inflammation, making it effective in detecting active lesions, edema, and ongoing inflammatory processes in the brain.

x. **FLAIR (Fluid-Attenuated Inversion Recovery):** FLAIR is an advanced MRI sequence that suppresses cerebrospinal fluid signals, thereby enhancing the visibility of lesions located near ventricles and cortical regions, which are common in MS.

xi. **Lesion Segmentation:** Lesion segmentation is the process of identifying, isolating, and outlining abnormal regions in medical images. It is essential for quantifying lesion size, distribution, and progression in MS studies.

xii. **Convolutional Neural Network (CNN):** A Convolutional Neural Network is a deep learning model specifically designed for image analysis. It automatically learns hierarchical features such as edges, textures, and complex patterns, making it suitable for medical image segmentation.

xiii. **3D Convolutional Neural Network (3D CNN):** A 3D CNN is an extension of traditional CNNs that processes volumetric data such as 3D MRI scans. It captures spatial relationships across multiple slices, improving accuracy in detecting complex lesion structures.

xiv. **Deep Learning:** Deep Learning is a subset of artificial intelligence that utilizes multi-layered neural networks to learn patterns and representations from large datasets without manual feature engineering.

xv. **Feature Extraction:** Feature extraction is the process of automatically identifying relevant patterns or characteristics from input data. In medical imaging, it includes detecting edges, textures, shapes, and lesion-specific features.

xvi. **Volumetric Quantification:** Volumetric quantification refers to the measurement of lesion volume, count, and spatial distribution within the brain. It provides objective metrics for assessing disease progression and treatment effectiveness.

xvii. **Class Imbalance:** Class imbalance occurs when one category of data (e.g., healthy tissue) significantly outweighs another (e.g., lesion regions). This imbalance can negatively affect model training and lead to biased predictions.

xviii. **Dice Similarity Coefficient (DSC):** The Dice Similarity Coefficient is a statistical evaluation metric used to measure the overlap between predicted segmentation and ground truth. It is widely used to assess the accuracy of medical image segmentation models.

xix. **Attention Mechanism:** An attention mechanism is a deep learning technique that enables a model to focus on the most relevant regions of input data, improving the detection of important features such as small or subtle lesions.

xx. **Domain Shift:** Domain shift refers to differences in data distributions caused by variations in imaging protocols, scanner types, or patient populations. It can reduce the generalization ability of machine learning models across datasets.

CHAPTER TWO
LITERATURE REVIEW

2.0 Introduction

Multiple Sclerosis (MS) is a chronic neurological disorder that affects the central nervous system, particularly the brain and spinal cord. The disease is characterized by inflammation, demyelination, and neurodegeneration, which result in the formation of lesions within the white matter and gray matter of the brain. Magnetic Resonance Imaging (MRI) has become one of the most important imaging modalities for diagnosing and monitoring Multiple Sclerosis because it provides detailed visualization of brain tissues and lesion structures. However, manual identification and segmentation of MS lesions from MRI scans remain difficult, time-consuming, and highly dependent on radiologists' expertise. Due to the increasing number of MRI scans generated in clinical practice, there is a growing need for automated and intelligent systems capable of accurately identifying and segmenting MS lesions.

Recent advances in Artificial Intelligence (AI), particularly Deep Learning and Convolutional Neural Networks (CNNs), have significantly transformed medical image analysis. CNN-based architectures have shown remarkable performance in feature extraction, pattern recognition, and image segmentation tasks. In Multiple Sclerosis research, CNNs have been widely adopted for automated lesion segmentation because they can learn complex spatial features directly from MRI data without relying heavily on handcrafted features. Furthermore, the emergence of 3D CNN architectures has improved the ability of models to capture volumetric contextual information from MRI scans, leading to better segmentation accuracy and lesion detection.

This study reviews existing studies related to the use of Convolutional Neural Networks for Multiple Sclerosis lesion segmentation in MRI images. The review focuses on deep learning techniques, CNN architectures, 3D MRI segmentation approaches, U-Net models, attention mechanisms, transfer learning strategies, and automated lesion detection systems. The chapter also identifies gaps in existing studies and highlights the relevance of the proposed research.

2.1 Related Works

Raab et al. (2023) investigated an efficient multi-modal Convolutional Neural Network for Multiple Sclerosis lesion detection using different MRI modalities. The study integrated FLAIR, T1-weighted, and T2-weighted MRI sequences to improve lesion visibility and segmentation accuracy. Their proposed framework demonstrated that combining multiple MRI modalities improved feature extraction and enabled the CNN model to detect lesions with varying intensity levels. The researchers concluded that multi-modal MRI analysis significantly enhances lesion segmentation performance and reduces the risk of missing subtle lesion regions.

Gao et al. (2025) developed a fully automatic FLAIR MRI segmentation system for Multiple Sclerosis diagnosis using Convolutional Neural Networks. The study emphasized the importance of FLAIR MRI because it effectively highlights white matter abnormalities associated with Multiple Sclerosis. Their CNN model automatically segmented lesion regions with minimal human intervention and achieved high segmentation accuracy. The researchers noted that automated lesion segmentation can reduce radiologists' workload and improve consistency in MRI interpretation.

Jain et al. (2022) proposed a lesion volume quantification framework using two Convolutional Neural Networks for MRI analysis of Multiple Sclerosis patients. Their approach focused on improving lesion boundary detection and volumetric analysis. The researchers demonstrated that accurate lesion volume estimation is essential for monitoring disease progression and assessing treatment effectiveness. Their framework improved segmentation precision and reduced errors associated with manual volumetric measurements.

Valverde et al. (2017) introduced a cascaded 3D Fully Convolutional Neural Network approach for detecting new lesions in Multiple Sclerosis patients. Their architecture consisted of two CNN stages, where the first stage identified possible lesion regions while the second stage refined segmentation results and reduced false positives. The study demonstrated that cascaded 3D CNN models improve sensitivity and enhance the detection of small lesions that are difficult to identify using traditional methods.

Liu et al. (2025) proposed a Multi-Pathway 3D CNN integrated with Conditional Random Fields for automated segmentation of Multiple Sclerosis lesions in MRI scans. Their architecture processed MRI images through multiple pathways to capture both local and global contextual information. The Conditional Random Field component improved segmentation smoothness and

preserved lesion boundaries. Their findings showed that combining 3D CNNs with probabilistic graphical models enhances segmentation reliability.

Ronneberger et al. (2015) developed the U-Net architecture for biomedical image segmentation. The encoder-decoder structure with skip connections enabled precise localization and segmentation of medical images. U-Net became one of the most widely adopted architectures in medical image analysis because of its ability to preserve spatial information and generate accurate segmentation masks. Many subsequent Multiple Sclerosis lesion segmentation models were built upon the U-Net framework.

Zhou et al. (2023) proposed a modified U-Net architecture for automated segmentation of Multiple Sclerosis lesions in brain MRI images. Their model incorporated additional convolutional layers and optimization strategies to improve feature extraction. The study achieved higher Dice similarity scores and improved lesion localization compared to traditional segmentation approaches. The researchers concluded that modified U-Net architectures are highly effective for complex medical image segmentation tasks.

Wang et al. (2023) introduced GAU U-Net for Multiple Sclerosis segmentation. Their model integrated Global Attention Units into the U-Net architecture to improve the network's focus on lesion regions while suppressing irrelevant background information. The study demonstrated that attention mechanisms significantly improve lesion sensitivity and segmentation accuracy, particularly for small and irregularly shaped lesions.

Zhang et al. (2024) investigated brain lesion segmentation using deep learning for computer-aided differential diagnosis of Multiple Sclerosis and Neuromyelitis Optica. Their CNN-based framework analyzed lesion characteristics and spatial distributions to distinguish between neurological disorders. The study demonstrated that deep learning models can support clinicians by improving diagnostic accuracy and reducing diagnostic ambiguity.

Roy et al. (2019) developed DeepLesionBrain, a deep learning framework designed to improve generalization in Multiple Sclerosis lesion segmentation. The study emphasized the importance of training CNN models on diverse MRI datasets collected from different imaging centers. Their approach improved robustness across heterogeneous datasets and reduced performance degradation caused by scanner variability.

Salem et al. (2022) proposed a VGG-UNet framework for segmentation and evaluation of Multiple Sclerosis lesions in MRI slices. Their hybrid architecture combined the feature extraction capabilities of VGG networks with the segmentation strength of U-Net. The framework achieved improved segmentation accuracy and enhanced lesion boundary delineation. Their findings highlighted the effectiveness of combining pretrained feature extractors with encoder-decoder segmentation models.

Mou et al. (2023) investigated Bayesian identification of Multiple Sclerosis using 3D Convolutional Neural Networks. Their research introduced probabilistic CNN models capable of estimating uncertainty during lesion prediction. The Bayesian framework improved segmentation reliability by providing confidence estimates for lesion classifications. This approach is important in clinical environments where uncertainty estimation supports medical decision-making.

Shah et al. (2024) compared automatic lesion detection using 2D- and 3D-FLAIR MRI datasets. Their study revealed that 3D MRI scans provide superior spatial continuity and better lesion representation compared to 2D scans. The researchers observed that 3D MRI volumes improve CNN performance by preserving anatomical relationships across slices, resulting in higher segmentation precision.

Li et al. (2023) proposed MS-DASPNet, a deep learning architecture integrating dual attention mechanisms, spatial pyramid pooling, and transfer learning for Multiple Sclerosis lesion segmentation. Their model improved feature representation and captured contextual information at multiple scales. The study demonstrated that transfer learning enhances segmentation performance when training data are limited.

Zeng et al. (2022) explored the use of Convolutional Neural Networks for segmentation of Multiple Sclerosis lesions in 3D MRI images. Their study showed that deep CNN architectures outperform traditional image processing techniques because they automatically learn hierarchical spatial features from MRI volumes. The researchers emphasized that CNNs reduce the need for handcrafted feature engineering while improving segmentation accuracy.

Kamnitsas et al. (2017) proposed a deep multi-scale 3D CNN combined with Conditional Random Fields for brain lesion segmentation. Their architecture extracted features at different scales to capture both detailed lesion structures and broader anatomical context. The integration of

Conditional Random Fields improved boundary refinement and reduced segmentation noise. The study became one of the foundational works in deep learning-based medical image segmentation.

The reviewed studies collectively demonstrate that deep learning and Convolutional Neural Networks have significantly improved automated Multiple Sclerosis lesion segmentation. Existing approaches have achieved notable success in lesion detection, boundary delineation, volumetric analysis, and multi-modal MRI integration. However, challenges such as class imbalance, limited annotated datasets, computational complexity, low-contrast lesion detection, and poor generalization across different MRI protocols remain major research concerns. These limitations highlight the need for more robust, accurate, and clinically interpretable CNN-based segmentation frameworks for Multiple Sclerosis lesion analysis in 3D MRI images.

2.1.1 Summary of Related Works

Authors/Year	Results and Findings	Limitations of the Study
Raab et al. (2023)	Developed an efficient multi-modal CNN for Multiple Sclerosis lesion detection using FLAIR, T1-	The model required large multi-modal datasets and high computational resources. Generalization

	weighted, and T2-weighted MRI sequences. The study improved lesion visibility, segmentation accuracy, and feature extraction by combining multiple MRI modalities.	across different MRI scanners remained challenging.
Gao et al. (2025)	Proposed a fully automatic FLAIR MRI segmentation system using CNNs. The model achieved high segmentation accuracy and reduced the workload of radiologists during MRI analysis.	The study focused mainly on FLAIR images and did not extensively evaluate multi-modal MRI integration. Performance could be affected by image noise and poor MRI quality.
Jain et al. (2022)	Introduced a lesion volume quantification framework using dual CNN architectures. The study improved lesion boundary detection and volumetric measurement accuracy.	The framework required high-quality annotated data and struggled with extremely small lesion regions. Computational complexity was also high.
Valverde et al. (2017)	Developed a cascaded 3D Fully Convolutional Neural Network for detecting new MS lesions. The approach improved lesion sensitivity and reduced false positives.	The model required extensive training time and large GPU memory because of the multi-stage CNN architecture.

Liu et al. (2025)	Proposed a Multi-Pathway 3D CNN integrated with Conditional Random Fields for automated lesion segmentation. The study improved segmentation smoothness and lesion boundary consistency.	The integration of CRFs increased computational complexity and processing time during training and inference.
Ronneberger et al. (2015)	Developed the U-Net architecture for biomedical image segmentation. The encoder-decoder structure improved localization and segmentation accuracy.	Original U-Net was designed mainly for 2D medical images and had limitations in capturing volumetric contextual information from 3D MRI data.
Wang et al. (2023)	Introduced GAU U-Net with Global Attention Units for Multiple Sclerosis segmentation. The model improved focus on lesion regions and enhanced segmentation accuracy for small lesions.	Attention mechanisms increased the complexity of the network and required more training data to avoid overfitting.
Zhang et al. (2024)	Developed a CNN-based framework for differential diagnosis of Multiple	The framework required large and diverse datasets for reliable disease

	Sclerosis and Neuromyelitis Optica. The model improved diagnostic support through lesion pattern analysis.	differentiation and was computationally intensive.
Roy et al. (2019)	Proposed DeepLesionBrain to improve generalization in MS lesion segmentation. The study improved robustness across MRI datasets from different imaging centers.	Performance still decreased when tested on highly heterogeneous datasets with different scanning protocols.
Salem et al. (2022)	Developed a VGG-UNet framework combining VGG feature extraction with U-Net segmentation. The model improved lesion boundary delineation and segmentation precision.	The hybrid architecture increased training complexity and required longer training time.
Mou et al. (2023)	Investigated Bayesian 3D CNNs for Multiple Sclerosis identification. The approach provided uncertainty estimation during lesion prediction, improving reliability.	Bayesian models required higher computational power and more complex optimization strategies.
Shah et al. (2024)	Compared lesion detection using 2D- and 3D-FLAIR	3D MRI processing demanded greater memory

	MRI datasets. The study showed that 3D MRI scans provided better spatial continuity and improved lesion representation.	and computational resources than 2D MRI analysis.
Li et al. (2023)	Proposed MS-DASPNet with dual attention mechanisms, spatial pyramid pooling, and transfer learning. The model improved segmentation accuracy and feature representation.	The architecture was computationally expensive and depended heavily on pretrained models and large datasets.
Zeng et al. (2022)	Investigated CNN-based segmentation of Multiple Sclerosis lesions in 3D MRI images. The study showed CNNs outperform traditional image processing methods in segmentation accuracy.	CNN models required large annotated datasets and faced challenges in detecting low-contrast lesions.
Kamnitsas et al. (2017)	Proposed a deep multi-scale 3D CNN combined with Conditional Random Fields for brain lesion segmentation. The model improved lesion boundary refinement and reduced segmentation noise.	The architecture had high computational cost and required significant GPU memory for processing 3D MRI volumes.

2.2 Concept of Lesions and Multiple Sclerosis Lesions

2.2.1 Concept of Lesions

Lesions are abnormal areas of tissue damage or structural change that occur in different parts of the body as a result of injury, infection, inflammation, or disease processes. In medical imaging and neurology, lesions are commonly associated with abnormalities found in the brain, spinal cord, or other organs. According to Zhang et al. (2024), lesions in Multiple Sclerosis are areas where the protective myelin sheath surrounding nerve fibers becomes damaged due to autoimmune activity. These damaged regions interfere with the normal transmission of electrical signals within the nervous system, leading to neurological symptoms such as muscle weakness, vision problems, fatigue, impaired coordination, and cognitive dysfunction.

In Multiple Sclerosis, lesions are primarily formed because the immune system mistakenly attacks the myelin sheath, resulting in inflammation, demyelination, and scar tissue formation. These lesions can appear in different regions of the central nervous system, including the brain, optic nerves, and spinal cord. Shah et al. (2024) explained that the appearance, size, and location of lesions vary significantly among patients, making diagnosis and disease monitoring complex. Some lesions may remain inactive for long periods, while others become active and continue to grow, contributing to disease progression and neurological disability.

Magnetic Resonance Imaging (MRI) plays a critical role in detecting and analyzing lesions because it provides detailed visualization of brain tissues and structural abnormalities. Gao et al. (2025) noted that MRI sequences such as FLAIR, T1-weighted, and T2-weighted imaging are highly effective for identifying Multiple Sclerosis lesions. FLAIR MRI is particularly useful because it suppresses cerebrospinal fluid signals, thereby making white matter lesions more visible. T1-weighted images help identify chronic lesions and tissue degeneration, while T2-weighted images highlight inflammatory regions and lesion burden.

Lesions are generally categorized based on their activity, appearance, and pathological characteristics. Active lesions are associated with ongoing inflammation and are often enhanced

after contrast injection during MRI scans. Chronic lesions, on the other hand, represent long-term tissue damage and may indicate irreversible neurological impairment. Jain et al. (2022) emphasized that accurate lesion quantification and segmentation are important for evaluating disease progression, monitoring treatment response, and assessing patient prognosis.

The segmentation of lesions refers to the process of identifying and separating lesion regions from surrounding healthy tissues within MRI images. Manual lesion segmentation by radiologists is time-consuming, subjective, and prone to inter-observer variability. As a result, researchers have increasingly explored automated lesion segmentation methods using Artificial Intelligence and Convolutional Neural Networks. Valverde et al. (2017) demonstrated that CNN-based lesion segmentation systems can improve lesion detection accuracy and reduce false positives by learning complex spatial patterns from MRI scans.

Deep learning approaches have significantly improved lesion analysis because they automatically learn hierarchical features directly from imaging data. Li et al. (2023) explained that advanced CNN architectures equipped with attention mechanisms and spatial pyramid pooling can effectively identify lesions of different sizes, shapes, and intensities. These methods enhance segmentation precision and improve the reliability of automated diagnostic systems.

Despite advancements in lesion segmentation, several challenges remain. Lesions may vary greatly in size, intensity, and morphology, making accurate detection difficult. Small or low-contrast lesions can easily be missed, especially in noisy MRI scans. In addition, variations in MRI acquisition protocols across medical institutions can affect lesion visibility and model generalization. Roy et al. (2019) highlighted that robust lesion segmentation systems must be trained on diverse MRI datasets to improve performance across different imaging environments.

However, lesions are important pathological indicators in Multiple Sclerosis diagnosis and disease monitoring. Accurate detection and segmentation of lesions are essential for evaluating disease progression, planning treatment, and improving patient outcomes. The integration of MRI imaging with Convolutional Neural Networks has significantly advanced automated lesion analysis, providing more accurate, efficient, and reliable methods for Multiple Sclerosis lesion segmentation.

2.2.2 Concept of Multiple Sclerosis Lesions

Multiple Sclerosis (MS) lesions are abnormal areas of damaged tissue that occur within the central nervous system as a result of inflammation, demyelination, and neurodegeneration. These lesions develop when the immune system mistakenly attacks the myelin sheath, which is the protective covering surrounding nerve fibers in the brain and spinal cord. The destruction of myelin disrupts the normal transmission of electrical signals between nerve cells, leading to various neurological impairments. According to Zhang et al. (2024), MS lesions are considered one of the major pathological indicators used in diagnosing and monitoring the progression of Multiple Sclerosis because their presence reflects ongoing inflammatory and degenerative processes within the nervous system.

MS lesions are commonly found in the white matter regions of the brain, although they can also occur in gray matter and the spinal cord. The lesions vary greatly in terms of size, shape, location, and intensity, depending on the stage and severity of the disease. Shah et al. (2024) explained that lesions located near the ventricles, optic nerves, brainstem, and spinal cord are particularly common in Multiple Sclerosis patients. The variability in lesion appearance makes accurate detection and segmentation difficult, especially when lesions are small or have low contrast against surrounding brain tissues.

Magnetic Resonance Imaging has become the most important imaging technique for detecting and analyzing Multiple Sclerosis lesions because it provides detailed visualization of brain abnormalities. Gao et al. (2025) noted that MRI sequences such as FLAIR, T1-weighted, and T2-weighted imaging are highly effective in identifying lesion regions. FLAIR MRI is particularly useful because it suppresses cerebrospinal fluid signals and enhances the visibility of white matter lesions. T2-weighted images highlight inflammatory lesions and edema, while T1-weighted images help identify chronic lesions and tissue degeneration commonly referred to as “black holes.”

MS lesions are generally classified into active lesions and chronic lesions. Active lesions are associated with ongoing inflammation and blood-brain barrier disruption. These lesions often appear enhanced after contrast injection during MRI scanning and indicate current disease activity. Chronic lesions, on the other hand, represent long-term tissue damage and permanent demyelination. Jain et al. (2022) emphasized that chronic lesions are strongly associated with neurological disability and disease progression in Multiple Sclerosis patients.

The formation of MS lesions follows a complex pathological process involving immune cell infiltration, inflammation, demyelination, axonal damage, and gliosis. During the early stages of lesion formation, immune cells such as T-cells and macrophages penetrate the blood-brain barrier and attack myelin-producing cells called oligodendrocytes. This inflammatory response leads to tissue swelling and myelin destruction. Over time, repeated inflammatory attacks can result in irreversible neuronal damage and brain atrophy. Roy et al. (2019) highlighted that understanding lesion development is essential for improving disease diagnosis, treatment planning, and long-term patient management.

2.3 Methods of Diagnosing lesion and Multiple Lesion Sclerosis

Multiple Sclerosis (MS) is a chronic neurological disorder that affects the central nervous system, particularly the brain and spinal cord. Because the symptoms of MS are similar to those of many other neurological diseases, accurate diagnosis requires a combination of clinical examination, medical history evaluation, imaging techniques, and laboratory investigations. Early and accurate diagnosis is important because it allows timely treatment, helps reduce disease progression, and improves patient quality of life. According to Zhang et al. (2024), the diagnosis of Multiple Sclerosis involves identifying evidence of lesions that are disseminated in both time and space within the central nervous system.

1. **Clinical Examination and Medical History:** One of the first methods used in diagnosing Multiple Sclerosis is clinical evaluation. Neurologists examine the patient's symptoms, reflexes, muscle coordination, balance, vision, and sensory responses. Common symptoms of MS include fatigue, muscle weakness, numbness, blurred vision, dizziness, impaired coordination, and cognitive difficulties. The physician also reviews the patient's medical history to determine whether neurological symptoms have occurred at different times and affected different parts of the body. Clinical examination alone is often insufficient for diagnosis because MS symptoms vary significantly among patients and may resemble other neurological disorders.
2. **Magnetic Resonance Imaging (MRI):** Magnetic Resonance Imaging (MRI) is considered the most important and widely used method for diagnosing Multiple Sclerosis. MRI provides detailed images of the brain and spinal cord, allowing clinicians to identify lesions caused by demyelination. Gao et al. (2025) explained that MRI sequences such as FLAIR, T1-weighted, and T2-weighted imaging are highly effective for detecting MS lesions. FLAIR MRI is especially useful because it suppresses cerebrospinal fluid signals and enhances the visibility

of white matter lesions. T2-weighted MRI helps identify areas of inflammation and lesion burden, while T1-weighted MRI is useful for detecting chronic lesions and tissue degeneration. MRI is also valuable for monitoring disease progression and evaluating treatment effectiveness over time.

3. **McDonald Criteria:** The McDonald Criteria is one of the standard diagnostic frameworks used for Multiple Sclerosis diagnosis. The criteria combine clinical findings, MRI evidence, and laboratory results to determine whether lesions are disseminated in space and time. Dissemination in space means that lesions are present in different regions of the central nervous system, while dissemination in time means that lesions developed at different periods. The McDonald Criteria improve diagnostic accuracy and allow earlier diagnosis compared to older methods.
4. **Lumbar Puncture (Spinal Tap):** Lumbar puncture is another important diagnostic method for Multiple Sclerosis. During this procedure, cerebrospinal fluid (CSF) is collected from the spinal canal and analyzed in the laboratory. The presence of oligoclonal bands in the cerebrospinal fluid may indicate abnormal immune system activity associated with MS. Although lumbar puncture alone cannot confirm Multiple Sclerosis, it provides supportive evidence when combined with MRI findings and clinical evaluation.
5. **Evoked Potential Tests:** Evoked potential tests measure the electrical activity of the brain in response to sensory stimulation. These tests evaluate how quickly and effectively nerve signals travel through the nervous system. Since Multiple Sclerosis damages the myelin sheath surrounding nerve fibers, nerve signal transmission becomes slower. Visual evoked potential tests are commonly used because vision problems are frequent in MS patients. Delayed nerve responses may indicate demyelination even before symptoms become severe.
6. **Blood Tests:** Blood tests are often performed to rule out other diseases that may produce symptoms similar to Multiple Sclerosis. Conditions such as lupus, vitamin deficiencies, infections, and neuromyelitis optica can mimic MS symptoms. Although there is currently no specific blood test that directly confirms Multiple Sclerosis, blood analysis helps eliminate alternative diagnoses and supports the overall diagnostic process.
7. **Artificial Intelligence and Deep Learning Approaches:** Recent advances in Artificial Intelligence and Deep Learning have introduced automated methods for diagnosing Multiple Sclerosis. Convolutional Neural Networks (CNNs) are increasingly used for lesion detection and MRI segmentation. Valverde et al. (2017) demonstrated that CNN-based systems can automatically identify lesion regions with high accuracy and reduce false positives. Similarly,

Li et al. (2023) proposed attention-based deep learning frameworks capable of improving lesion segmentation and disease classification.

Automated CNN systems improve diagnostic efficiency by reducing manual analysis time and providing more consistent lesion detection. These methods are particularly useful for analyzing large volumes of MRI data and identifying subtle lesion patterns that may be difficult for human observers to detect.

2.4 Machine Learning Methods for Diagnosing Multiple Sclerosis

Machine Learning (ML) has become an essential component in modern medical diagnostics, particularly in the detection and analysis of neurological disorders such as Multiple Sclerosis (MS). It enables computer systems to learn patterns from medical data and make predictions without being explicitly programmed. In MS diagnosis, machine learning techniques are widely applied to MRI image analysis, lesion detection, disease classification, and progression monitoring. These methods improve diagnostic efficiency by assisting clinicians in interpreting complex imaging data and identifying subtle abnormalities that may not be easily visible to the human eye.

Supervised learning methods are among the most commonly used approaches in MS diagnosis. These methods rely on labeled datasets where MRI scans are annotated as either showing MS lesions or not. Algorithms such as Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression are frequently applied. SVM is particularly effective in handling high-dimensional medical imaging data by finding an optimal decision boundary between classes. Random Forest improves classification accuracy by combining multiple decision trees, thereby reducing overfitting and improving stability. However, these traditional methods depend heavily on handcrafted feature extraction, such as texture, intensity, and shape features, which limits their ability to fully capture complex lesion structures compared to deep learning approaches (Shah et al., 2024).

Unsupervised learning methods are used when labeled data is not available. These techniques aim to discover hidden patterns or structures within MRI datasets without predefined labels.

Common methods include K-means clustering, hierarchical clustering, and Gaussian Mixture Models. In Multiple Sclerosis analysis, clustering techniques can group similar brain regions based on pixel intensity or texture variations, which may help identify potential lesion areas. Although unsupervised learning is useful for exploratory analysis, it generally provides lower accuracy compared to supervised and deep learning methods due to the absence of ground truth guidance (Roy et al., 2019).

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have significantly advanced the field of MS diagnosis. CNNs automatically learn hierarchical features from MRI images without the need for manual feature engineering. This makes them highly effective for lesion detection and segmentation tasks. Studies such as Valverde et al. (2017) demonstrated that CNN-based models improve lesion detection accuracy by learning complex spatial patterns directly from MRI scans. Similarly, Li et al. (2023) showed that attention-based deep learning frameworks enhance segmentation performance by focusing on lesion-relevant regions while suppressing irrelevant background information. The introduction of 3D CNN models has further improved performance by enabling the analysis of volumetric MRI data, allowing better understanding of spatial relationships between slices. Gao et al. (2025) also emphasized that automated CNN-based FLAIR segmentation significantly improves diagnostic consistency in MS cases.

Hybrid machine learning methods combine traditional machine learning algorithms with deep learning models to improve performance and generalization. In such systems, CNNs are often used for feature extraction, while classifiers like SVM or Random Forest handle the final classification stage. This combination can be particularly useful in situations where datasets are limited or imbalanced. Hybrid approaches also improve interpretability by separating feature learning from decision-making. However, they may still require significant computational resources and careful model tuning to achieve optimal results (Jain et al., 2022).

Feature-based machine learning approaches were widely used before the rise of deep learning. These methods rely on extracting handcrafted features such as texture, shape, edge patterns, and intensity distributions from MRI images. Techniques like Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and wavelet transforms are commonly used for feature extraction. These features are then fed into classifiers such as SVM or decision trees. While these approaches can perform well in controlled settings, their reliance on manual

feature engineering limits their scalability and adaptability to complex medical imaging data (Zeng et al., 2022).

Despite the advancements in machine learning for Multiple Sclerosis diagnosis, several challenges still exist. A major limitation is the scarcity of large, high-quality labeled MRI datasets, which are essential for training accurate models. Class imbalance is another challenge, as lesion regions are often much smaller compared to healthy brain tissue, leading to biased predictions. Additionally, differences in MRI scanners, imaging protocols, and acquisition settings across hospitals can reduce model generalization and performance consistency. Deep learning models also require high computational power and large memory resources, making them difficult to deploy in low-resource clinical environments (Valverde et al., 2017; Roy et al., 2019).

However, machine learning methods have greatly improved the diagnosis and analysis of Multiple Sclerosis by enabling automated interpretation of MRI data. While traditional machine learning techniques provide foundational classification approaches, deep learning models such as CNNs and 3D CNNs deliver more accurate and robust performance in lesion detection and segmentation. However, ongoing challenges such as data limitations, computational requirements, and generalization issues must be addressed to fully integrate these systems into routine clinical practice.

2.4 Deep Learning Methods for Diagnosing Multiple Sclerosis

Deep learning methods have become the most powerful and widely adopted approach for diagnosing Multiple Sclerosis (MS), especially in the analysis of MRI brain images. Unlike traditional machine learning techniques that rely on manually extracted features, deep learning models automatically learn hierarchical representations directly from raw imaging data. This ability makes them highly effective for detecting complex lesion patterns, segmenting abnormal brain tissues, and supporting clinical decision-making. In MS diagnosis, deep learning is primarily used for lesion detection, lesion segmentation, disease classification, and progression monitoring.

Convolutional Neural Networks (CNNs) are the most commonly used deep learning models in Multiple Sclerosis diagnosis. CNNs are designed to process grid-like data such as images and are capable of learning spatial features through convolutional layers. According to Valverde et al. (2017), CNN-based models significantly improve lesion detection performance by learning

complex spatial patterns directly from MRI scans without requiring manual feature engineering. Similarly, Gao et al. (2025) demonstrated that CNN-based systems applied to FLAIR MRI images can automatically segment MS lesions with high accuracy, reducing radiologists' workload and improving diagnostic consistency.

Three-dimensional CNNs (3D CNNs) have further improved MS diagnosis by enabling the analysis of volumetric MRI data instead of individual slices. This allows the model to capture spatial relationships across multiple slices, leading to more accurate lesion segmentation. Shah et al. (2024) emphasized that 3D MRI-based CNN models provide better lesion continuity and spatial understanding compared to 2D approaches. This makes 3D CNNs particularly suitable for identifying small or irregular lesions that may be missed in traditional slice-based analysis.

Advanced CNN architectures such as U-Net and its variants are widely used in biomedical image segmentation due to their encoder-decoder structure and skip connections. The U-Net model enables precise localization of lesion regions while preserving spatial information. Zhou et al. (2023) proposed a modified U-Net model that improved lesion segmentation accuracy in brain MRI scans by enhancing feature extraction and optimization strategies. Similarly, Wang et al. (2023) introduced GAU U-Net, which integrates Global Attention Units to improve focus on lesion regions and suppress irrelevant background information, leading to better segmentation of small lesions.

Attention-based deep learning models have also gained significant importance in MS diagnosis. These models help the network focus on the most relevant regions of an image while ignoring less important background information. Li et al. (2023) developed MS-DASPNet, which incorporates dual attention mechanisms and spatial pyramid pooling to improve lesion detection across different scales. The study showed that attention mechanisms enhance feature representation and improve segmentation accuracy, especially for lesions with varying sizes and intensities.

Multi-modal deep learning approaches combine different MRI sequences such as FLAIR, T1-weighted, and T2-weighted images to improve lesion detection performance. Raab et al. (2023) demonstrated that integrating multiple MRI modalities enhances CNN performance by providing complementary information about lesion structure and tissue abnormalities. This approach improves robustness and reduces the risk of missing lesions that may not be visible in a single imaging modality.

Hybrid deep learning frameworks have also been explored to improve segmentation performance and generalization. These methods combine CNN-based feature extraction with other techniques such as Conditional Random Fields (CRFs) or probabilistic models. Liu et al. (2025) proposed a Multi-Pathway 3D CNN integrated with Conditional Random Fields, which improved lesion boundary refinement and segmentation consistency. This combination helps reduce noise and improves the accuracy of lesion detection in complex MRI scans.

Despite the strong performance of deep learning models, several challenges still exist. One major limitation is the need for large, high-quality labeled datasets, which are often difficult to obtain in medical imaging. Another challenge is the computational complexity of training deep neural networks, especially 3D CNNs, which require significant GPU memory and processing power. Additionally, variations in MRI acquisition protocols across different hospitals can affect model generalization and reduce performance in real-world clinical settings (Roy et al., 2019; Valverde et al., 2017).

In conclusion, deep learning methods have significantly transformed the diagnosis of Multiple Sclerosis by enabling accurate, automated analysis of MRI images. CNNs, 3D CNNs, U-Net architectures, and attention-based models have all contributed to improved lesion detection and segmentation performance. However, challenges such as data scarcity, computational cost, and generalization issues must be addressed to fully integrate deep learning systems into clinical practice.

2.6 Multiple Sclerosis Segmentation and Classification

Multiple Sclerosis (MS) segmentation and classification are two fundamental tasks in medical image analysis that support the diagnosis, monitoring, and treatment of the disease. Segmentation refers to the process of identifying and separating lesion regions from normal brain tissues in MRI scans, while classification involves determining whether a patient or image belongs to a specific disease category, such as MS or non-MS, or even classifying disease severity. These two tasks are closely related because accurate segmentation of lesions often improves classification performance by providing more meaningful features for decision-making.

2.6.1 Segmentation of Multiple Sclerosis Lesions

Multiple Sclerosis lesion segmentation focuses on detecting and outlining abnormal regions in brain MRI images caused by demyelination. This is a challenging task due to the irregular shape, small size, and low contrast of lesions compared to surrounding healthy tissues. Gao et al. (2025) explained that FLAIR MRI sequences are particularly effective for lesion segmentation because they suppress cerebrospinal fluid signals, making white matter lesions more visible. However, even with advanced imaging techniques, manual segmentation remains time-consuming and highly subjective, which has led to the development of automated approaches.

Deep learning methods, especially Convolutional Neural Networks (CNNs), have significantly improved lesion segmentation performance. Valverde et al. (2017) demonstrated that CNN-based segmentation models can detect new MS lesions with higher sensitivity and fewer false positives compared to traditional methods. Similarly, Zhou et al. (2023) showed that modified U-Net architectures improve segmentation accuracy by enhancing feature extraction and preserving spatial information through skip connections. Wang et al. (2023) further improved segmentation performance using GAU U-Net, where attention mechanisms helped the model focus on lesion regions while ignoring irrelevant background structures.

Three-dimensional CNNs have also been widely adopted for MS lesion segmentation because they process volumetric MRI data rather than individual slices. Shah et al. (2024) noted that 3D MRI-based segmentation improves lesion continuity and spatial consistency, making it easier to detect small or scattered lesions. In addition, hybrid models such as Multi-Pathway CNNs with Conditional Random Fields (CRFs) improve boundary refinement and reduce segmentation noise (Liu et al., 2025).

2.6.2 Classification of Multiple Sclerosis

Multiple Sclerosis classification involves categorizing MRI scans or patient data into disease-related classes such as MS vs non-MS or different stages of disease progression. Classification models use features extracted from MRI images, either manually or through deep learning techniques. Traditional machine learning methods such as Support Vector Machines (SVM) and Random Forests have been used for classification tasks, but their performance depends heavily on handcrafted feature engineering.

Deep learning-based classification methods have shown superior performance because they automatically learn discriminative features from raw MRI data. Li et al. (2023) demonstrated that

attention-based CNN models improve classification accuracy by focusing on the most relevant lesion regions. Similarly, Zhang et al. (2024) developed deep learning frameworks capable of distinguishing Multiple Sclerosis from other neurological diseases such as Neuromyelitis Optica by analyzing lesion patterns and spatial distribution.

Multi-modal MRI-based classification approaches also improve performance by combining different imaging sequences such as FLAIR, T1-weighted, and T2-weighted scans. Raab et al. (2023) found that multi-modal CNN models provide richer feature representations, which enhance classification accuracy and robustness across different patient datasets.

2.6.3 Relationship Between Segmentation and Classification

Segmentation and classification are strongly interconnected in Multiple Sclerosis diagnosis. Accurate lesion segmentation provides detailed information about lesion size, location, and distribution, which are essential features for classification models. Poor segmentation can negatively affect classification accuracy by introducing noise or irrelevant features. Jain et al. (2022) emphasized that precise lesion volume quantification improves disease monitoring and classification reliability.

Deep learning frameworks often integrate both segmentation and classification tasks into a single pipeline. This end-to-end approach allows the model to learn both spatial lesion features and disease-level patterns simultaneously, improving overall diagnostic performance.

2.6.4 Challenges in MS Segmentation and Classification

Despite advancements in deep learning, several challenges remain. MS lesions vary widely in size, shape, and intensity, making consistent segmentation difficult. Small lesions and low-contrast regions are often missed by automated systems. In addition, class imbalance between lesion and non-lesion pixels affects model performance.

Another major challenge is the variability in MRI acquisition protocols across hospitals, which reduces model generalization. Roy et al. (2019) highlighted that models trained on limited datasets may not perform well on unseen clinical data. Furthermore, deep learning models require large computational resources and high-quality annotated datasets, which are often difficult to obtain.

Overall, Multiple Sclerosis segmentation and classification are essential components of automated disease diagnosis using MRI imaging. While segmentation focuses on identifying lesion regions, classification determines disease presence or stage. Deep learning methods, particularly CNNs, 3D CNNs, and attention-based architectures, have significantly improved both tasks. However, challenges such as data scarcity, lesion variability, and computational demands must be addressed to develop more robust and clinically applicable systems.

2.7 Concept of Convolutional Neural Network

Convolutional Neural Network (CNN) is a type of deep learning algorithm specifically designed for processing image data and recognizing spatial patterns within images. CNNs are widely used in computer vision, medical image analysis, object detection, facial recognition, and image segmentation because of their ability to automatically learn important features from raw image inputs. In the field of medical imaging, CNNs have become one of the most effective techniques for diagnosing diseases such as Multiple Sclerosis through MRI image analysis.

A Convolutional Neural Network is inspired by the structure of the human visual system. Unlike traditional machine learning methods that rely on manually extracted features, CNNs automatically learn hierarchical features directly from images during training. This ability allows CNNs to identify complex patterns, textures, edges, and lesion structures within MRI images more effectively than conventional approaches. According to Valverde et al. (2017), CNNs significantly improve lesion detection accuracy because they can automatically capture spatial and contextual information from MRI scans.

CNN architecture is composed of several interconnected layers that work together to process image data. The major layers include the convolutional layer, pooling layer, activation layer, and fully connected layer. Each layer performs a specific function in extracting and learning image features.The convolutional layer is the core component of a CNN. It applies small filters known as kernels across the input image to detect important features such as edges, textures, and shapes. During this process, feature maps are generated, which represent important spatial patterns in the image. In Multiple Sclerosis diagnosis, convolutional layers help detect lesion regions and abnormalities in MRI scans.

Activation functions are applied after convolution operations to introduce non-linearity into the network. One of the most commonly used activation functions is the Rectified Linear Unit

(ReLU), which helps the network learn complex relationships within image data. Without activation functions, the CNN would behave like a simple linear model and would not effectively capture complex lesion patterns.Pooling layers are used to reduce the spatial dimensions of feature maps while preserving important information. This process decreases computational complexity and helps prevent overfitting. Max pooling is commonly used in CNN architectures, where the maximum value within a small region of the feature map is selected. Pooling improves the network's ability to recognize lesions regardless of slight variations in size or position.

The fully connected layer is usually located near the end of the CNN architecture. It combines the features extracted from previous layers and performs classification tasks. In Multiple Sclerosis diagnosis, the fully connected layer may classify MRI images as either containing MS lesions or not. The output layer often uses activation functions such as Softmax or Sigmoid depending on the classification problem.

CNNs are highly effective for medical image analysis because they automatically learn hierarchical feature representations. Early layers detect simple patterns such as edges and textures, while deeper layers learn more complex structures such as lesion shapes and spatial distributions. Gao et al. (2025) demonstrated that CNN-based segmentation systems improve the accuracy and consistency of detecting Multiple Sclerosis lesions in FLAIR MRI images.

Different CNN architectures have been developed to improve image segmentation and classification performance. U-Net is one of the most widely used CNN architectures in medical imaging because of its encoder-decoder structure and skip connections that preserve spatial information. Zhou et al. (2023) showed that modified U-Net architectures improve lesion segmentation accuracy in brain MRI images. Similarly, Wang et al. (2023) proposed GAU U-Net, which integrates attention mechanisms into CNN architecture to improve focus on lesion regions and suppress irrelevant background information.

Three-dimensional CNNs (3D CNNs) have further advanced MRI analysis by processing volumetric MRI data instead of individual slices. This allows the model to capture spatial relationships across multiple image slices, improving lesion continuity and segmentation accuracy. Shah et al. (2024) explained that 3D CNN models are more suitable for detecting Multiple Sclerosis lesions because they preserve anatomical information within MRI volumes.

Despite their advantages, CNNs also face several limitations. Training deep CNN models requires large annotated datasets and high computational resources such as GPUs. Overfitting may occur when training data are limited, reducing model generalization to new datasets. In addition, variations in MRI acquisition protocols across hospitals may affect CNN performance. Roy et al. (2019) emphasized the importance of training CNN models on diverse datasets to improve robustness and generalization.

Overall, Convolutional Neural Networks are powerful deep learning models designed for image analysis and pattern recognition. Their ability to automatically learn hierarchical image features has made them highly effective for Multiple Sclerosis lesion detection, segmentation, and classification using MRI images. Advanced CNN architectures such as U-Net, attention-based CNNs, and 3D CNNs continue to improve the accuracy and reliability of automated medical image analysis systems.

2.8 CNN Methods for Diagnosing Multiple Sclerosis

Convolutional Neural Networks (CNNs) have become one of the most effective deep learning approaches for diagnosing Multiple Sclerosis (MS) through the analysis of Magnetic Resonance Imaging (MRI) scans. CNNs are capable of automatically learning important spatial and structural features from MRI images without requiring manual feature extraction. Their ability to identify complex lesion patterns, tissue abnormalities, and spatial relationships has significantly improved the accuracy of automated MS diagnosis systems. According to Valverde et al. (2017), CNN-based methods outperform many traditional machine learning techniques in lesion detection and segmentation because they can effectively learn hierarchical representations directly from medical images.

One of the most commonly used CNN methods in MS diagnosis is the two-dimensional Convolutional Neural Network (2D CNN). In this method, MRI slices are processed individually, allowing the network to learn lesion characteristics from each slice separately. 2D CNNs are computationally efficient and require less memory compared to volumetric approaches. They are often applied to FLAIR MRI images because these images enhance lesion visibility. Gao et al. (2025) demonstrated that 2D CNN-based systems achieve high segmentation accuracy in automatic FLAIR MRI lesion detection. However, 2D CNNs may fail to capture spatial continuity between slices, which can reduce segmentation performance for complex lesions.

Three-dimensional Convolutional Neural Networks (3D CNNs) are advanced CNN methods designed to process volumetric MRI data instead of individual image slices. These models analyze spatial information across multiple MRI slices simultaneously, allowing better understanding of lesion structures and continuity. Shah et al. (2024) explained that 3D CNN models provide improved lesion localization and segmentation accuracy because they preserve anatomical relationships within MRI volumes. Similarly, Mou et al. (2023) utilized Bayesian 3D CNNs for Multiple Sclerosis identification and demonstrated that volumetric CNN models improve diagnostic reliability while also providing uncertainty estimation during prediction.

Fully Convolutional Networks (FCNs) are another important CNN-based method used in MS diagnosis and lesion segmentation. Unlike traditional CNNs that use fully connected layers for classification, FCNs perform pixel-level classification, making them highly suitable for image segmentation tasks. Valverde et al. (2017) proposed a cascaded 3D Fully Convolutional Neural Network approach that improved the detection of new MS lesions by reducing false positives and increasing lesion sensitivity. FCNs are particularly useful for generating precise lesion boundaries in MRI images.

U-Net is one of the most widely adopted CNN architectures for biomedical image segmentation. The U-Net architecture consists of an encoder-decoder structure with skip connections that preserve spatial information during feature extraction and reconstruction. Zhou et al. (2023) demonstrated that modified U-Net architectures improve lesion segmentation accuracy in brain MRI images by enhancing feature extraction capabilities. Similarly, Wang et al. (2023) introduced GAU U-Net, which integrates Global Attention Units into the U-Net architecture to improve focus on lesion regions and suppress irrelevant background information. These attention-based CNN methods significantly improve the detection of small and irregular lesions.

Attention-based CNN models are increasingly used in MS diagnosis because they allow the network to focus on the most important regions of MRI images. Attention mechanisms improve feature representation by highlighting lesion-relevant areas while reducing the influence of irrelevant structures. Li et al. (2023) developed MS-DASPNet, which combines dual attention mechanisms and spatial pyramid pooling to improve lesion segmentation accuracy. Their study demonstrated that attention modules improve multi-scale feature learning and enhance lesion detection performance in heterogeneous MRI datasets.

Multi-modal CNN methods combine different MRI modalities such as FLAIR, T1-weighted, and T2-weighted images to improve diagnostic performance. Raab et al. (2023) investigated an efficient multi-modal CNN framework and found that combining multiple MRI sequences improves lesion visibility and segmentation accuracy. Multi-modal CNNs provide complementary information about brain tissues and lesions, allowing better feature extraction and reducing the risk of missing subtle abnormalities.

Hybrid CNN methods combine CNN architectures with other techniques such as Conditional Random Fields (CRFs), transfer learning, or probabilistic models. Liu et al. (2025) proposed a Multi-Pathway 3D CNN integrated with Conditional Random Fields to improve lesion boundary refinement and segmentation consistency. Transfer learning approaches are also widely used to improve CNN performance when labeled datasets are limited. These hybrid methods improve model generalization and reduce overfitting.

Despite their effectiveness, CNN methods for diagnosing Multiple Sclerosis still face several challenges. One major limitation is the need for large annotated MRI datasets for effective training. Deep CNN architectures also require high computational power and GPU resources, especially for 3D MRI processing. Additionally, variations in MRI acquisition protocols across hospitals can reduce model generalization and affect segmentation accuracy. Roy et al. (2019) emphasized the importance of training CNN models on diverse datasets to improve robustness and adaptability across different imaging environments.

In conclusion, CNN methods have significantly improved the automated diagnosis and segmentation of Multiple Sclerosis lesions using MRI images. Techniques such as 2D CNNs, 3D CNNs, Fully Convolutional Networks, U-Net architectures, attention-based CNNs, and multi-modal CNN approaches have demonstrated high accuracy in lesion detection and classification. However, challenges such as data scarcity, computational complexity, and variability in MRI protocols remain important areas for future research and development.

2.9 Summary of Chapter

Multiple Sclerosis (MS) is a chronic neurological disorder that affects the central nervous system through inflammation, demyelination, and lesion formation within the brain and spinal

cord. Magnetic Resonance Imaging (MRI) was identified as one of the most effective imaging techniques for detecting and monitoring MS lesions because of its ability to provide detailed visualization of brain structures and abnormalities. However, manual lesion segmentation is time-consuming, subjective, and highly dependent on radiologists' expertise, thereby creating the need for automated and intelligent diagnostic systems capable of improving accuracy and efficiency in lesion detection and analysis.

Several studies reviewed demonstrated the importance of deep learning and Convolutional Neural Networks (CNNs) in Multiple Sclerosis lesion segmentation and classification. Different CNN architectures such as U-Net, Fully Convolutional Networks (FCNs), 2D CNNs, 3D CNNs, attention-based CNNs, and hybrid CNN frameworks have shown remarkable performance in lesion detection, boundary delineation, volumetric analysis, and disease classification. Advanced approaches involving attention mechanisms, transfer learning, Conditional Random Fields, and multi-modal MRI integration were also found to improve segmentation accuracy, reduce false positives, and enhance model robustness. Despite these advancements, challenges such as class imbalance, limited annotated MRI datasets, computational complexity, low-contrast lesion detection, and poor generalization across different MRI acquisition protocols still remain major research concerns.

The review also explained the concepts of lesions and Multiple Sclerosis lesions, emphasizing their pathological characteristics, formation processes, and importance in disease diagnosis and progression monitoring. Different methods for diagnosing Multiple Sclerosis were discussed, including clinical examination, MRI analysis, lumbar puncture, evoked potential tests, and the McDonald Criteria. In addition, machine learning and deep learning methods used in MS diagnosis were examined, showing that deep learning approaches, particularly CNN-based systems, outperform traditional machine learning methods because they automatically learn hierarchical features directly from MRI data without relying heavily on handcrafted feature extraction.

Overall, Convolutional Neural Networks have significantly transformed automated medical image analysis for Multiple Sclerosis diagnosis and lesion segmentation. CNN-based models, especially 3D CNNs and attention-based architectures, provide improved lesion localization, segmentation precision, and classification performance when applied to MRI brain images. However, further research is still necessary to address challenges related to data scarcity,

computational requirements, variability in MRI protocols, and the development of more robust and clinically interpretable automated segmentation systems.

CHAPTER THREE
RESEARCH METHODOLOGY

3.0 Introduction

This chapter presents the methodology adopted for the development and evaluation of a deep learning-based framework for the segmentation of Multiple Sclerosis (MS) lesions in three-dimensional (3D) Magnetic Resonance Imaging (MRI) scans. The methodology provides a systematic description of the procedures followed throughout the research, including the research design, dataset acquisition, data preprocessing, model development, implementation, training, and performance evaluation. The study adopts a quantitative experimental research design using a supervised deep learning approach, where a 3D U-Net model is trained to automatically identify and segment MS lesions from volumetric MRI images. The MRI dataset used for this study consists of T1-weighted, T2-weighted, and FLAIR brain MRI images, together with expert-annotated lesion segmentation masks obtained from a publicly available dataset. Prior to model training, the MRI volumes undergo preprocessing operations such as image loading, intensity normalization, resizing to a uniform dimension, mask preparation, and dataset partitioning into training, validation, and testing subsets. These preprocessing steps improve data quality, ensure consistency across the dataset, and enhance the learning capability and generalization performance of the deep learning model.

The implementation of the proposed framework is carried out using Python programming language in the Google Colaboratory environment with TensorFlow and Keras as the primary deep learning libraries. The 3D U-Net architecture is selected because of its encoder-decoder structure and skip connections, which enable effective extraction of both local and global volumetric features while preserving spatial information necessary for accurate lesion segmentation. During training, the model learns the complex patterns that distinguish lesion tissues from healthy brain tissues through iterative optimization over multiple epochs. To monitor the learning process and prevent overfitting, validation data and callback techniques are incorporated during model training. The performance of the developed model is evaluated using standard medical image segmentation metrics, including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), accuracy, precision, recall, confusion matrix, Receiver Operating Characteristic (ROC) curve, Area Under the ROC Curve (AUC), and Precision-Recall (PR) curve. These evaluation metrics provide a comprehensive assessment of the model's segmentation

accuracy, reliability, and ability to generalize to unseen MRI data. Overall, this chapter establishes the methodological foundation of the study and explains the procedures employed to develop an efficient and reliable automated system for Multiple Sclerosis lesion segmentation in 3D MRI images.

3.1 Overview of Proposed System Architecture and Flow chart

The proposed system architecture is designed to automatically segment Multiple Sclerosis (MS) lesions from three-dimensional (3D) Magnetic Resonance Imaging (MRI) scans using a 3D U-Net deep learning model. The architecture provides an end-to-end automated framework that accepts preprocessed MRI volumes as input and produces segmented lesion masks as output. Unlike traditional image processing techniques that depend on handcrafted feature extraction and manual lesion identification, the proposed architecture automatically learns hierarchical and spatial features directly from MRI data through deep learning. This significantly improves segmentation accuracy, minimizes human intervention, and provides a reliable tool for assisting clinicians in the diagnosis and monitoring of Multiple Sclerosis.

The architecture consists of seven major components, namely MRI Dataset Acquisition, Data Preprocessing, Dataset Partitioning, 3D U-Net Network, Model Training, Lesion Segmentation Prediction, and Performance Evaluation. These components work together sequentially to ensure that the MRI images are properly prepared, processed, analyzed, and evaluated. Figure 3.1 illustrates the overall architecture of the proposed system.

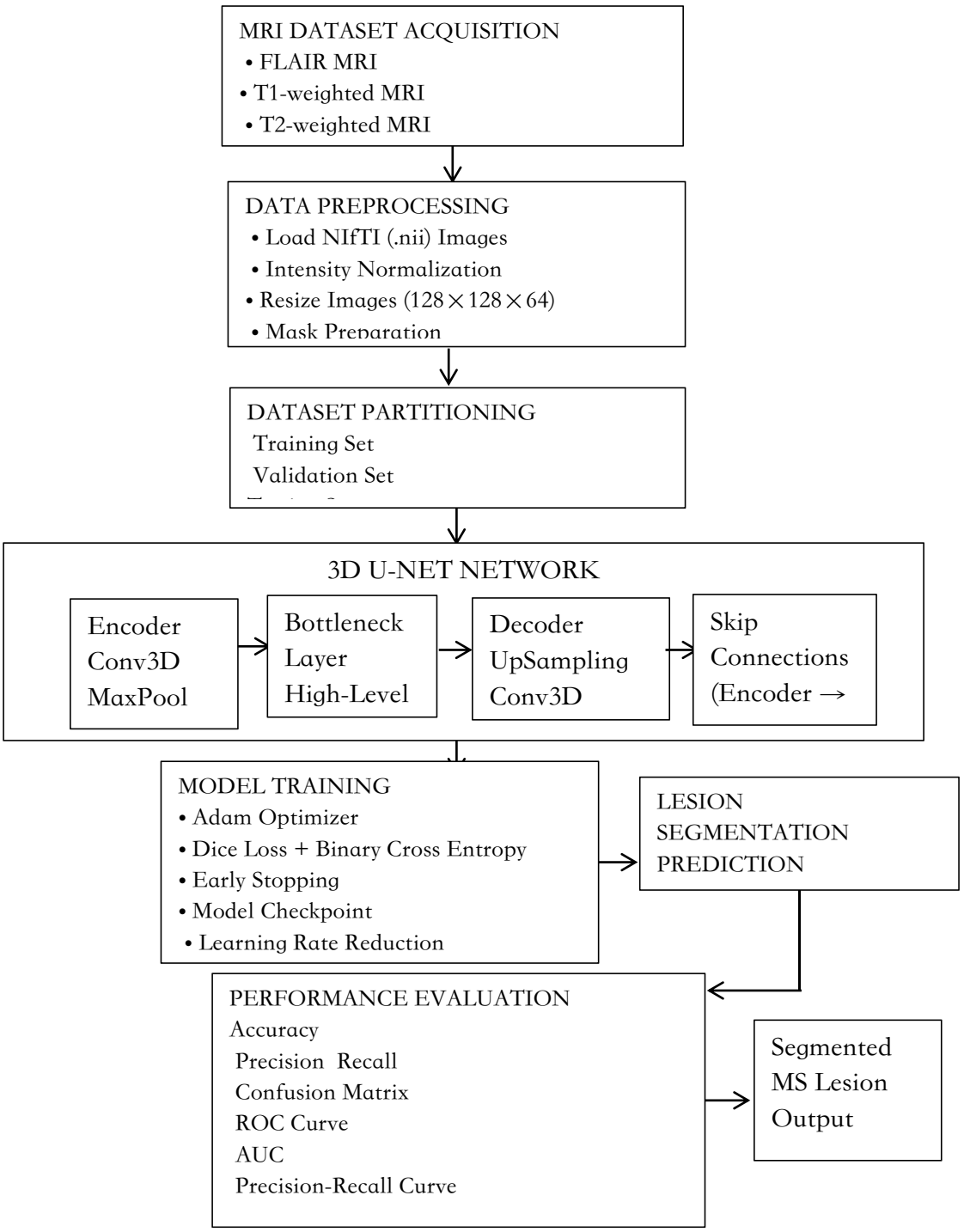


Figure 3.1 Proposed System Architetcture

1. MRI Dataset Acquisition

The first stage of the proposed architecture involves acquiring the MRI dataset required for training and evaluating the deep learning model. The dataset used in this research consists of brain MRI scans obtained from a publicly available medical imaging repository. Each patient folder contains three MRI modalities, namely FLAIR (Fluid Attenuated Inversion Recovery), T1-weighted, and T2-weighted images, together with manually annotated lesion segmentation masks prepared by experienced radiologists. These lesion masks serve as the ground truth labels during supervised learning.

2. Data Preprocessing

The MRI volumes collected from different patients often have variations in image intensity, spatial resolution, orientation, and size due to differences in MRI scanners and acquisition protocols. These inconsistencies may negatively affect the learning capability of the deep learning model. Consequently, preprocessing is performed to standardize the dataset before training. The preprocessing stage begins by loading the MRI images stored in NIfTI (.nii) format using specialized medical imaging libraries. Each MRI volume is then normalized so that voxel intensity values fall within a consistent numerical range. Image normalization improves numerical stability during model training and accelerates convergence by preventing extremely large intensity values from dominating the learning process.

3. Dataset Partitioning

Once preprocessing has been completed, the prepared dataset is divided into three subsets: the training dataset, validation dataset, and testing dataset. Dataset partitioning is essential because it enables the model to learn from one subset while being evaluated on previously unseen data.The training dataset contains the largest portion of the MRI images and is used to train the 3D U-Net model. During training, the model gradually learns the complex relationship between MRI images and lesion masks by adjusting its internal parameters through backpropagation.The validation dataset is used during training to monitor the model's learning progress. After each training epoch, the validation data are used to determine whether the model is improving or beginning to overfit the training data. Techniques such as Early Stopping and Reduce Learning Rate rely on validation performance to optimize the training process.The testing dataset is reserved until the training process has been completed. It contains MRI scans that have never been seen by the model during

learning. Evaluating the model on the testing dataset provides an unbiased assessment of its ability to generalize to new patients and determines its practical usefulness in real clinical environments.Proper dataset partitioning reduces overfitting, improves model reliability, and provides realistic estimates of segmentation performance.

4. 3D U-Net Architecture

The 3D U-Net architecture serves as the core component of the proposed system. It is specifically designed for volumetric medical image segmentation and processes complete three-dimensional MRI volumes rather than individual two-dimensional slices. This enables the network to capture spatial relationships across adjacent slices, which is particularly important for accurately identifying Multiple Sclerosis lesions. The architecture consists of three major sections: the encoder, the bottleneck, and the decoder, connected through skip connections. The encoder performs feature extraction using multiple three-dimensional convolutional layers followed by activation functions and max-pooling operations. During each convolution operation, small filters move across the MRI volume and learn important features such as edges, textures, lesion boundaries, and tissue characteristics. As the network progresses deeper, the pooling layers reduce the spatial dimensions while increasing the number of feature maps. This allows the model to capture increasingly abstract representations of lesion structures while reducing computational requirements.

5. Model Training

Following network construction, the 3D U-Net model is trained using the prepared MRI dataset. During training, batches of MRI volumes are passed through the network, and predicted segmentation masks are generated. These predictions are compared with the manually annotated ground truth masks using a suitable loss function. The model employs the Adam optimizer, which efficiently updates the network weights through gradient descent. A combination of Dice Loss and Binary Cross-Entropy Loss is used to minimize segmentation errors. Dice Loss is particularly effective for medical image segmentation because it directly maximizes the overlap between predicted lesion regions and the ground truth masks while addressing the class imbalance problem commonly observed in lesion datasets.

6. Lesion Segmentation Prediction

After training has been completed, the optimized model is used to predict lesion masks for previously unseen MRI scans. Each input MRI volume passes through the trained 3D U-Net, which performs voxel-wise classification by assigning every voxel to either the lesion class or the background class. The output is a binary segmentation mask that accurately outlines the size, shape, and location of Multiple Sclerosis lesions within the brain. This automated segmentation significantly reduces the time required for manual lesion delineation and improves consistency in clinical diagnosis.

7. Performance Evaluation

The final stage of the proposed architecture evaluates the performance of the developed segmentation model. The predicted lesion masks are compared with the expert-annotated ground truth masks using several quantitative evaluation metrics. The Dice Similarity Coefficient (DSC) measures the degree of overlap between the predicted segmentation and the ground truth. Intersection over Union (IoU) evaluates the ratio of the overlapping region to the combined area of the predicted and actual lesions. Precision measures the proportion of predicted lesion voxels that are truly lesions, while Recall measures the proportion of actual lesion voxels successfully detected by the model. Accuracy provides the overall percentage of correctly classified voxels. To further assess classification performance, a Confusion Matrix is generated to display the numbers of true positives, true negatives, false positives, and false negatives. In addition, the Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and Precision-Recall Curve are computed to evaluate the model's discrimination ability across different classification thresholds. Together, these metrics provide a comprehensive assessment of the effectiveness, robustness, and clinical applicability of the proposed 3D U-Net segmentation framework.

3.1.1 Flow chart

The following flowchart provides a visual representation of the proposed system's workflow, illustrating the sequence of steps from data collection to performance and evaluation. Figure 3.2 below illustrates the flowchart of the proposed system

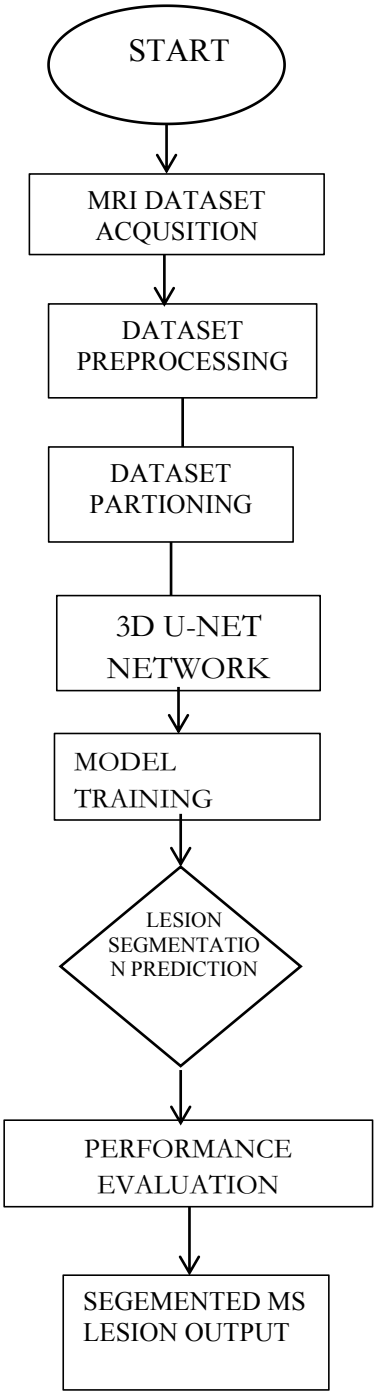


Figure 3.2 Flow chart of the Proposed system

3.2 Data Collection and Preprocessing

The data collection and preprocessing stage forms the foundation of the proposed Multiple Sclerosis (MS) lesion segmentation framework, as the quality of the input data directly influences the performance of the deep learning model. In this study, the MRI dataset was obtained from a publicly available medical imaging repository containing brain MRI scans of 60 patients diagnosed with Multiple Sclerosis. The dataset includes three-dimensional (3D) T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (FLAIR) MRI images, together with expert-annotated lesion segmentation masks stored in NIfTI (.nii) format. Among the available modalities, the FLAIR MRI images and their corresponding lesion masks were utilized because FLAIR provides enhanced visualization of MS lesions by suppressing cerebrospinal fluid signals, making lesion regions more distinguishable from surrounding healthy brain tissues. Before the images were supplied to the proposed 3D U-Net model, several preprocessing operations were carried out to ensure data consistency and improve model performance. These operations included loading the MRI volumes and lesion masks, image normalization, resizing all images to a uniform dimension of 128 × 128 × 64 voxels, converting the lesion masks into binary format, pairing each MRI image with its corresponding ground truth mask, and partitioning the dataset into training, validation, and testing subsets. These preprocessing procedures standardized the dataset, reduced computational complexity, improved numerical stability during training, and prepared the MRI volumes for efficient learning and accurate segmentation by the proposed deep learning model.

3.2.1 Data Source

The dataset used in this study was downloaded from Kaggle, where it is made available from the original Mendeley Data repository. The dataset, titled "Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information," contains MRI scans of 60 Multiple Sclerosis patients, including T1-weighted, T2-weighted, and FLAIR images, together with expert-annotated lesion segmentation masks. The dataset was originally published by Ali M. Muslim (2022) on Mendeley Data and is widely used for research on automated Multiple Sclerosis lesion segmentation (Muslim, A. M. (2022). *Brain MRI Dataset of Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information* (Version 1). Mendeley Data. https://doi.org/10.17632/8bctsm8jz7.1). The MRI scans are stored in Neuroimaging Informatics Technology Initiative (NIfTI) format with the .nii file extension, which preserves the three-dimensional anatomical structure of the brain and is widely used in medical image analysis.

The dataset consists of three MRI modalities, namely T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (FLAIR) images, together with their corresponding expert-annotated lesion segmentation masks. The lesion masks were created through a consensus of experienced radiologists and a neurologist, providing reliable ground truth labels for supervised learning. In addition to the MRI images, the dataset includes patient clinical information such as the Expanded Disability Status Scale (EDSS) score and other demographic and clinical metadata. However, this study focuses primarily on the MRI volumes and their corresponding lesion masks for automated lesion segmentation. Among the available MRI modalities, the FLAIR images and their corresponding lesion segmentation masks were selected for this research because FLAIR imaging provides superior visualization of Multiple Sclerosis lesions by suppressing cerebrospinal fluid signals, thereby increasing the contrast between lesion regions and normal brain tissues. This enhanced visibility enables the proposed 3D U-Net model to learn discriminative lesion features more effectively and produce more accurate segmentation results.

3.2.2 Data Acquisition Procedure and Paramters

Data Acquisition Procedure

The data acquisition procedure involved obtaining a publicly available Multiple Sclerosis (MS) brain MRI dataset from Kaggle, where it is distributed from the original Mendeley Data repository. The dataset was selected because it provides high-quality three-dimensional (3D) MRI scans accompanied by expert-annotated lesion segmentation masks, making it suitable for supervised deep learning-based lesion segmentation. After downloading the compressed dataset, it was extracted into the working directory and organized according to the predefined folder structure. The dataset consists of 60 patient folders, with each folder representing a unique patient and containing multiple MRI modalities and their corresponding lesion segmentation masks stored in Neuroimaging Informatics Technology Initiative (NIfTI) format (.nii). Each patient folder contains T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (FLAIR) MRI images, together with manually annotated lesion masks corresponding to each imaging modality. For the purpose of this study, the FLAIR MRI images and their corresponding FLAIR lesion segmentation masks were selected because FLAIR imaging provides superior visualization of Multiple Sclerosis lesions by suppressing cerebrospinal fluid signals, thereby improving lesion contrast against normal brain tissues.

Data Parameters:

The dataset used in this study contains both imaging and annotation data required for the automated segmentation of Multiple Sclerosis (MS) lesions. Each patient record consists of three-dimensional (3D) brain Magnetic Resonance Imaging (MRI) volumes acquired using different imaging modalities, together with manually annotated lesion segmentation masks. The MRI images are stored in Neuroimaging Informatics Technology Initiative (NIfTI) format (.nii), which preserves volumetric information and is widely adopted in medical image analysis. For this research, the FLAIR MRI images and their corresponding lesion segmentation masks were selected as the primary input because they provide enhanced visualization of MS lesions. During preprocessing, all MRI volumes and lesion masks were resized to a uniform dimension of 128 × 128 × 64 voxels and normalized to improve model performance.The major data parameters used in this study are presented in Table 3.1.

Table 3.1: Data Parameters Used in the Study

Parameter	Description

Dataset Name	Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information
Source	Kaggle (Originally from Mendeley Data)
Number of Patients	60
Imaging Modalities	T1-weighted, T2-weighted, FLAIR
Image Format	NIfTI (.nii)
Annotation Type	Expert-annotated lesion segmentation masks
Selected Mask	FLAIR Lesion Segmentation Mask
Image Dimension (After Preprocessing)	128 × 128 × 64 voxels
Number of Channels	1 (Grayscale)
Segmentation Type	Binary Segmentation (Lesion / Background)
Input Data	3D FLAIR MRI Volume
Output Data	Binary Lesion Segmentation Mask
Deep Learning Model	3D U-Net

3.2.3 Data Preprocessing

Data preprocessing was carried out to prepare the MRI dataset for training the proposed 3D U-Net model and to ensure consistency across all input images. Since MRI scans obtained from different patients may vary in image dimensions and intensity values, preprocessing was necessary to improve data quality and enhance model performance. The FLAIR MRI images and their corresponding lesion segmentation masks were loaded from the NIfTI (.nii) files using the Nibabel library. The MRI volumes were then resized to a uniform dimension of 128 × 128 × 64 voxels to ensure compatibility with the 3D U-Net architecture. Subsequently, the image intensity values were normalized to a range between 0 and 1 to reduce intensity variations and improve the stability and convergence of the learning process. The lesion masks were converted into binary images, where lesion regions were assigned a value of 1 and background regions were assigned a value of 0.

After preprocessing, each MRI volume was paired with its corresponding lesion segmentation mask to create input-output samples for supervised learning. A single channel dimension was added to the MRI images and masks, resulting in an input shape of 128 × 128 × 64 × 1 suitable for three-dimensional convolutional operations. The processed dataset was then partitioned into training, validation, and testing subsets using the train_test_split() function from the Scikit-learn library. This partitioning ensured that the model was trained on one subset of the data, validated during the learning process to reduce overfitting, and finally evaluated on previously unseen MRI scans. These preprocessing procedures produced a standardized and well-organized dataset, thereby improving the efficiency, robustness, and segmentation performance of the proposed 3D U-Net model.

3.2.4 Data Cleaning

Data cleaning is the first step performed after acquiring the MRI dataset and involves removing irrelevant, corrupted, or non-informative files that may affect the performance of the proposed 3D U-Net model. The downloaded dataset is examined to ensure that only valid patient folders containing the required MRI images and lesion segmentation masks are retained. Irrelevant system-generated files, such as the hidden .DS_Store file, are removed because they do not contain any medical imaging information and cannot be processed by the deep learning model. The dataset is also checked for duplicate patient records, corrupted image files, incomplete folders, and missing MRI modalities or lesion masks. This verification process ensures that the dataset is complete, consistent, and suitable for model development.

After removing irrelevant files, each patient folder is carefully inspected to verify that the corresponding FLAIR MRI image and FLAIR lesion segmentation mask are correctly matched. Since this study focuses on FLAIR images for lesion segmentation, only the FLAIR MRI volumes and their associated lesion masks are selected for subsequent preprocessing and model training. In addition, the lesion masks are verified to ensure they contain valid binary values, where :

i. Lesion regions are represented by 1
ii. Background regions are represented by 0.

This verification is necessary because the 3D U-Net performs binary segmentation and requires correctly labeled ground truth masks during supervised learning. These data cleaning procedures improve data integrity, eliminate inconsistencies, and ensure that only high-quality MRI images are used for training, validation, and testing the proposed segmentation model.

3.2.5 Data Normalization and Noise Reduction

1. Data Normalization (Image Normalization):

Data normalization is performed to ensure that the MRI images have a consistent range of intensity values before being used to train the proposed 3D U-Net model. MRI scans acquired from different scanners or imaging protocols often exhibit variations in pixel intensity, which can negatively affect the learning process of deep learning models. Therefore, normalization is applied to standardize the voxel intensity values across all MRI volumes, allowing the model to learn more effectively from the input data.

In this study, the intensity values of the FLAIR MRI images are normalized by scaling the voxel values to a range between 0 and 1. This normalization is achieved by dividing each voxel value by the maximum intensity value within the corresponding MRI volume. The normalization process provides the following benefits:

1. Scales voxel intensity values to the range 0–1.
2. Reduces intensity variations between MRI scans.
3. Improves numerical stability during model training.
4. Accelerates convergence of the Adam optimizer.

5. Enhances the segmentation performance and generalization ability of the 3D U-Net model.

Without normalization, variations in MRI intensity values may slow down the optimization process and reduce the overall accuracy of lesion segmentation.

2. Noise Reduction:

Noise reduction is performed to improve the quality, consistency, and reliability of the MRI dataset before model training. In medical imaging, noise refers to unwanted image artifacts, irrelevant files, inconsistencies, or variations that may interfere with the model's ability to accurately identify Multiple Sclerosis lesions. Reducing these sources of noise enables the model to focus on meaningful anatomical structures and lesion characteristics.

In this study, noise reduction is achieved through:

1. Removal of irrelevant system-generated files such as .DS_Store.
2. Exclusion of incomplete or corrupted patient records.
3. Verification of correct pairing between each FLAIR MRI image and its corresponding lesion segmentation mask.
4. Resizing all MRI volumes and lesion masks to a uniform dimension of 128 × 128 × 64 voxels.
5. Normalization of image intensity values to reduce scanner-related variations.
6. Conversion of lesion masks into binary format, where lesion voxels are represented by 1 and background voxels are represented by 0.

These preprocessing steps improve data consistency, eliminate unnecessary variations, reduce computational complexity, and ensure that the proposed 3D U-Net model learns meaningful features from high-quality MRI data rather than irrelevant noise. This ultimately contributes to improved segmentation accuracy and model robustness.

3.3 Proposed Model, Training Algorithm and Implementation

The proposed Multiple Sclerosis (MS) lesion segmentation system is designed to automatically identify and segment lesion regions from three-dimensional (3D) brain Magnetic

Resonance Imaging (MRI) scans using a deep learning approach. The system utilizes FLAIR MRI volumes and their corresponding expert-annotated lesion segmentation masks obtained from a publicly available Multiple Sclerosis MRI dataset. The primary objective of the proposed model is to learn the spatial and contextual characteristics of MS lesions and accurately generate pixel-level segmentation masks that distinguish lesion tissues from normal brain tissues. Unlike conventional image processing techniques that rely on handcrafted features, the proposed system automatically extracts hierarchical features directly from MRI volumes using a 3D U-Net architecture.

The implementation process consists of several stages, including MRI data loading and preparation, image preprocessing, dataset partitioning, model construction, model training, lesion prediction, and performance evaluation. During preprocessing, the MRI images are normalized, resized to a uniform dimension, and paired with their corresponding lesion masks to ensure consistency throughout the learning process. The processed dataset is then divided into training, validation, and testing subsets using different partition ratios to investigate their effects on segmentation performance. The proposed 3D U-Net model is trained using supervised learning, where the MRI images serve as inputs and the manually annotated lesion masks serve as target outputs. Finally, the effectiveness of the proposed framework is evaluated using standard medical image segmentation metrics, including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Accuracy, Precision, Recall, Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and Precision-Recall Curve.

3.3.1 Data Loading and Preparation for the Model

The first stage of the implementation process involves loading the Multiple Sclerosis MRI dataset into the Python programming environment using the Nibabel library, which is specifically designed for reading medical images stored in Neuroimaging Informatics Technology Initiative (NIfTI) (.nii) format. The dataset is organized into individual patient folders, with each folder containing T1-weighted, T2-weighted, FLAIR MRI images, and their corresponding lesion segmentation masks. Since this study focuses on lesion segmentation using FLAIR MRI, only the FLAIR MRI volumes and their corresponding FLAIR lesion masks are selected for implementation.

During the preparation stage, the MRI images and lesion masks are loaded into memory and converted into numerical arrays suitable for deep learning. The MRI volumes are resized to a uniform dimension of 128 × 128 × 64 voxels to ensure compatibility with the 3D U-Net architecture. Image normalization is subsequently performed by scaling the voxel intensity values to the range of 0–1, while the lesion masks are converted into binary images, where lesion regions are represented by 1 and background regions by 0. Finally, each MRI volume is paired with its corresponding lesion segmentation mask, forming input-output samples required for supervised model training.

3.3.2 Image Preparation

Deep learning models require standardized image data to achieve reliable segmentation performance. Therefore, all MRI volumes undergo additional preparation before training. Each MRI volume is reshaped by adding a single channel dimension, producing an input size of 128 × 128 × 64 × 1, which is compatible with the three-dimensional convolutional layers used in the proposed 3D U-Net model. This reshaping ensures that the network correctly interprets the MRI volumes as grayscale volumetric images.

Similarly, the lesion masks are reshaped into the same dimensions as the MRI images to maintain spatial correspondence during supervised learning. Proper alignment between the MRI volumes and lesion masks is essential because the model learns by comparing the predicted segmentation mask with the expert-annotated ground truth mask during training. These preparation procedures improve data consistency and ensure efficient processing by the proposed deep learning framework.

3.3.3 Data Splitting

After image preparation, the processed MRI dataset is divided into training, validation, and testing subsets. Dataset partitioning is an essential step because it enables the model to learn from one subset while being evaluated on previously unseen MRI scans. The training dataset is used to optimize the parameters of the 3D U-Net model, the validation dataset monitors learning progress and prevents overfitting during training, while the testing dataset is reserved exclusively for evaluating the final segmentation performance. To investigate the influence of different training

data sizes on model performance, three dataset partition ratios are employed in this study. Table 3.2 presents the dataset partition strategies used during experimentation.

Table 3.2 Dataset Split Ratios

TRAINING	VALIDATION	TESTING
80%	10%	10%
70%	15%	15%
75%	10%	15%

The partition ratios are described as follows:

1. 80:10:10 Partition Ratio: In this configuration, 80% of the MRI dataset is allocated for model training, 10% is used for validation, and the remaining 10% is reserved for testing. This partition provides the largest training dataset, allowing the model to learn more comprehensive lesion characteristics while maintaining sufficient data for validation and testing.
2. 75:10:15 Partition Ratio: In this configuration, 75% of the dataset is allocated for training, 10% for validation, and 15% for testing. This ratio provides a balanced distribution between model learning and performance evaluation by increasing the number of unseen MRI volumes available for testing.
3. 70:15:15 Partition Ratio: In this configuration, 70% of the dataset is used for training, while 15% is allocated to validation and 15% to testing. Although fewer MRI volumes are available for training, the larger validation and testing datasets provide a more rigorous assessment of the model's generalization capability.

The partitioning process is implemented using the train_test_split() function from the Scikit-learn library with randomization and a fixed random seed to ensure reproducibility. Random sampling ensures that MRI volumes are distributed fairly across all subsets while minimizing sampling bias.

3.3.4 Dataset

The dataset used in this study is the Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information, a publicly available medical imaging dataset originally published on Mendeley Data and distributed through Kaggle. The dataset contains three-dimensional brain MRI scans of 60 patients diagnosed with Multiple Sclerosis. Each patient record includes T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (FLAIR) MRI volumes together with expert-annotated lesion segmentation masks. The MRI scans are stored in NIfTI (.nii) format, which preserves the volumetric anatomical information required for three-dimensional medical image analysis.

For this research, only the FLAIR MRI images and their corresponding FLAIR lesion segmentation masks are utilized because FLAIR imaging provides superior visualization of Multiple Sclerosis lesions by suppressing cerebrospinal fluid signals and enhancing lesion contrast. The dataset is therefore suitable for supervised deep learning segmentation, where the FLAIR MRI volumes serve as the input data and the manually annotated lesion masks serve as the target outputs. The availability of expert-generated ground truth masks enables the proposed 3D U-Net model to learn accurate lesion boundaries and produce reliable segmentation results for previously unseen MRI volumes.

3.3.5 Training Details

The training process for the proposed 3D U-Net model for Multiple Sclerosis (MS) lesion segmentation involved the following:

1. **Dataset:** The Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information sourced from Kaggle (originally from Mendeley Data) was used for model training and evaluation. The dataset contains 3D FLAIR, T1-weighted, and T2-weighted MRI scans of 60 patients, together with expert-annotated lesion segmentation masks. In this study, the FLAIR MRI images and their corresponding FLAIR lesion masks were used for model development because they provide enhanced visualization of MS lesions.

    i. Split the dataset into training (70%), validation (15%), and testing (15%) subsets.
    ii. Split the dataset into training (75%), validation (10%), and testing (15%) subsets.

iii. Split the dataset into training (80%), validation (10%), and testing (10%) subsets.

2. **Image Preprocessing:** Before training, all MRI volumes and lesion masks were resized to a uniform dimension of 128 × 128 × 64 voxels. The MRI images were normalized by scaling voxel intensity values to the range of 0–1, while the lesion masks were converted into binary images, where lesion regions were represented by 1 and background regions by 0.
3. **Deep Learning Model:** The proposed 3D U-Net architecture was employed as the segmentation model. The network consists of an encoder, bottleneck, and decoder connected through skip connections, enabling the extraction of hierarchical spatial features and accurate reconstruction of lesion segmentation masks.
4. **Optimizer:** The Adam optimizer was employed during model training because of its adaptive learning capability and efficient convergence when training deep convolutional neural networks.
5. **Loss Function:** A combination of Dice Loss and Binary Cross-Entropy (BCE) Loss was utilized to optimize the segmentation model. Dice Loss maximizes the overlap between the predicted lesion masks and the ground truth masks, while Binary Cross-Entropy improves voxel-wise classification accuracy. The combination of these loss functions effectively addresses class imbalance between lesion and background voxels.
6. **Training Parameters:** The model was trained for 100 epochs using a batch size of 2. During each epoch, the model processed batches of MRI volumes, generated predicted lesion masks, computed the segmentation loss, and updated the network parameters through backpropagation. Early Stopping, Model Checkpoint, Reduce Learning Rate on Plateau, and CSV Logger callbacks were incorporated to improve convergence, prevent overfitting, and save the best-performing model throughout the training process.

3.3.6 Model Implementation

The implementation phase involves translating the proposed 3D U-Net segmentation framework into executable code using Python and deep learning libraries. The implementation includes MRI data loading, preprocessing, dataset partitioning, model development, training, validation, prediction, and performance evaluation. The entire implementation was carried out using Google Colaboratory, which provides cloud-based GPU resources for training computationally intensive deep learning models.

3.3.6.1 Software and Tools

1. Programming Language

i. Python

Python was used as the primary programming language for implementing the proposed 3D U-Net segmentation model. It was selected because of its simplicity, flexibility, and extensive support for medical image analysis, deep learning, and scientific computing.

2. Key Libraries and Frameworks

1. For Deep Learning

i. TensorFlow

TensorFlow was used as the primary deep learning framework for building, training, and evaluating the proposed 3D U-Net model. It provides efficient implementations of three-dimensional convolutional neural networks and GPU acceleration for medical image segmentation.

ii. Keras

Keras was used as the high-level Application Programming Interface (API) within TensorFlow to construct the 3D U-Net architecture, define model layers, configure optimization algorithms, and manage the training process.

2. For Medical Image Processing

i. NiBabel

NiBabel was used to load and process MRI volumes stored in NIfTI (.nii) format. It enables efficient reading and manipulation of three-dimensional medical images required for deep learning applications.

3. For Data Handling

i. NumPy

NumPy was used for numerical computations, array manipulation, image reshaping, normalization, and mathematical operations throughout the implementation process.

ii. Scikit-learn

Scikit-learn was used for dataset partitioning using the train_test_split() function and for computing evaluation metrics such as ROC curves, AUC scores, confusion matrices, precision, recall, and accuracy.

4. For Model Evaluation and Visualization

i. Matplotlib

Matplotlib was used to visualize training and validation accuracy curves, loss curves, Dice coefficient curves, ROC curves, Precision-Recall curves, and sample segmentation outputs.

ii. Seaborn

Seaborn was employed to generate visually enhanced confusion matrices and statistical visualizations of the segmentation results.

3. Development Environment

i. Google Colaboratory (Google Colab)

Google Colaboratory was used as the implementation environment because it provides a cloud-based platform with GPU acceleration suitable for training deep learning models on volumetric MRI data. It also supports Python, TensorFlow, and the medical imaging libraries required for the proposed system.

3.3.7 Model Building

1. The proposed lesion segmentation model was developed using a 3D U-Net architecture designed specifically for volumetric medical image segmentation. The model receives 128 × 128 × 64 × 1 FLAIR MRI volumes as input and produces voxel-wise binary lesion segmentation masks as output.

2. During model construction, the encoder path was designed using multiple Conv3D, Batch Normalization, ReLU activation, and MaxPooling3D layers to extract hierarchical spatial features from the MRI volumes. A bottleneck layer captures high-level semantic information before the decoder reconstructs the segmentation mask through UpSampling3D and Conv3D layers.
3. Skip connections were incorporated between corresponding encoder and decoder layers to preserve fine anatomical details and improve lesion boundary localization. The final output layer employs a Sigmoid activation function to generate voxel-wise probabilities representing lesion and background classes.

3.3.8 Model Compilation

1. The proposed 3D U-Net model was compiled using the Adam optimizer, which adaptively updates model parameters during training and provides efficient convergence for deep learning applications.
2. A combined Dice Loss and Binary Cross-Entropy Loss function was adopted because the study focuses on binary segmentation of lesion and background voxels. Dice Loss improves overlap between predicted and ground truth masks, while Binary Cross-Entropy enhances voxel-level classification accuracy.
3. The model was evaluated using Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Binary Accuracy, Precision, and Recall as training metrics. These metrics provide comprehensive information regarding segmentation quality and learning progress throughout the training process.

3.3.9 Model Training

1. The proposed model was trained using three dataset partitioning strategies: 70:15:15, 75:10:15, and 80:10:10. These configurations were adopted to investigate the effect of different training dataset sizes on segmentation performance and model generalization.

2. The training process was conducted for 100 epochs, allowing the model to iteratively learn lesion characteristics from the MRI volumes and progressively improve segmentation accuracy through multiple passes over the training dataset.
3. A batch size of 2 was utilized during training because three-dimensional MRI volumes require substantial GPU memory. This batch size provided an appropriate balance between memory utilization and training efficiency while ensuring stable convergence.
4. During each training epoch, the model generated predicted lesion masks, computed the Dice Loss and Binary Cross-Entropy Loss, compared the predictions with the expert-annotated ground truth masks, and updated the network parameters using backpropagation. Model performance was continuously monitored using the validation dataset, while Early Stopping, Model Checkpoint, Reduce Learning Rate on Plateau, and CSV Logger callbacks were employed to prevent overfitting, optimize learning, and preserve the best-performing model for final evaluation.

3.4 Performance Metrics

Performance metrics are essential for evaluating the effectiveness and reliability of the proposed 3D U-Net model for Multiple Sclerosis (MS) lesion segmentation. After training the model, several evaluation measures were employed to assess its ability to accurately identify and segment lesion regions from three-dimensional (3D) brain MRI scans. These metrics provide quantitative evidence of the segmentation performance by comparing the predicted lesion masks with the expert-annotated ground truth masks. The evaluation metrics adopted in this study include Accuracy, Precision, Recall (Sensitivity), Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and Precision-Recall Curve.

1. **Accuracy:** Accuracy measures the overall proportion of correctly classified voxels in the MRI volume. It represents the percentage of lesion and background voxels that are correctly identified by the proposed segmentation model.

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + FalsePositive + False\ Negative} \quad (1)$$

2. **Precision:** Precision measures the proportion of correctly predicted lesion voxels among all voxels predicted as lesions. It indicates the ability of the model to minimize false positive predictions.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Postive} \quad (2)$$

3. **Recall (Sensitivity):** Recall, also known as Sensitivity, measures the proportion of actual lesion voxels that are correctly detected by the segmentation model. It evaluates the model's ability to identify MS lesions without missing affected regions.

$$\text{Recall} = \frac{True\ Positive}{True\ Postive + False\ Negative} \quad (3)$$

4. **Dice Similarity Coefficient (DSC): T**he Dice Similarity Coefficient (DSC) is one of the most widely used evaluation metrics for medical image segmentation. It measures the degree of overlap between the predicted lesion mask and the ground truth lesion mask. A Dice score of 1 indicates perfect overlap, while 0 indicates no overlap.
5. **Intersection over Union (IoU):** Intersection over Union (IoU), also known as the Jaccard Index, measures the overlap between the predicted lesion mask and the ground truth mask by comparing their intersection with their union.
6. **Confusion Matrix:** The confusion matrix is a tabular representation of the segmentation results. It summarizes the number of correctly and incorrectly classified voxels by comparing the predicted segmentation mask with the ground truth mask. The confusion matrix provides detailed information about true positives, false positives, false negatives, and true negatives, allowing a comprehensive assessment of segmentation performance.

$$\text{Confusion Matrix} = \begin{pmatrix} True\ postive & Fasle\ postive \\ False\ negative & True\ Negative \end{pmatrix} \quad (4)$$

7. **Receiver Operating Characteristic (ROC) Curve:** The Receiver Operating Characteristic (ROC) Curve is a graphical representation used to evaluate the discrimination ability of the proposed segmentation model at different probability thresholds. The ROC curve plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 − Specificity). A curve closer to the upper-left corner indicates better segmentation performance.

8. **Area Under the Curve (AUC):** The Area Under the ROC Curve (AUC) measures the overall ability of the proposed model to distinguish lesion voxels from background voxels. The AUC value ranges from 0 to 1, where a value closer to 1 indicates excellent segmentation performance, while a value of 0.5 indicates random prediction.
9. **Precision–Recall (PR) Curve:** The Precision–Recall (PR) Curve illustrates the trade-off between precision and recall across different probability thresholds. It is particularly useful for medical image segmentation because lesion voxels usually represent a much smaller proportion of the MRI volume than background voxels, resulting in class imbalance. A PR curve closer to the upper-right corner indicates better segmentation performance, demonstrating that the model maintains high precision while successfully detecting most lesion regions.

3.5 Summary of Chapter

This chapter presented the methodology adopted for the development and implementation of the proposed 3D U-Net-based Multiple Sclerosis lesion segmentation system. It began by describing the overall research design, followed by the data collection process using the publicly available Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information. The chapter also discussed the data acquisition procedure, dataset characteristics, preprocessing techniques, data cleaning, image normalization, and noise reduction methods employed to prepare the MRI images for deep learning. These preprocessing procedures ensured that the MRI volumes were standardized, normalized, resized, and properly organized before model training.

Furthermore, the chapter described the proposed system architecture, implementation process, model building, model compilation, and training procedures adopted for the study. The implementation was carried out using Python, TensorFlow, Keras, NiBabel, Scikit-learn, NumPy, Matplotlib, and other supporting libraries within the Google Colaboratory environment. The dataset was partitioned into three different training, validation, and testing configurations (70:15:15, 75:10:15, and 80:10:10) to investigate the effect of different data distributions on segmentation performance. Finally, the chapter presented the performance evaluation metrics used to assess the effectiveness of the proposed model, including Accuracy, Precision, Recall, Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and Precision-Recall Curve. The next chapter presents the experimental results, performance analysis, discussion of findings,

and comparison of the segmentation performance obtained using the different dataset partitioning strategies.

CHAPTER FOUR
SIMULTAION RESULT AND DISCUSSION

4.0 Introduction

This chapter presents the results obtained from implementing and evaluating the proposed 3D U-Net model for the automated segmentation of Multiple Sclerosis (MS) lesions from three-dimensional (3D) brain Magnetic Resonance Imaging (MRI) scans. The experiments were conducted using the publicly available Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information, with FLAIR MRI images and their corresponding expert-annotated lesion masks serving as the input and ground truth data, respectively. The implementation was carried out using Python in the Google Colaboratory environment, while the model was trained and evaluated using three different dataset partitioning strategies: 70:15:15, 65:15:20, and 80:10:10, to investigate the effect of different training data sizes on segmentation performance.

The chapter presents the experimental findings obtained from the training and testing phases of the proposed model. The performance of the 3D U-Net is evaluated using quantitative metrics, including Accuracy, Precision, Recall, Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), Precision–Recall Curve, and the Confusion Matrix. In addition, graphical results such as the training and validation accuracy curves, loss curves, Dice coefficient curves, confusion matrices, ROC curves, and sample lesion segmentation outputs are presented and analyzed. A comparative discussion of the results obtained from the three dataset partitioning strategies is also provided to identify the configuration that achieved the best segmentation performance and to assess the effectiveness of the proposed model for automated Multiple Sclerosis lesion segmentation.

4.1 Simulation Results and Interpretation

The simulation ws done using three dfferent partition ratios, following this pattern {Training, Validation, Testing}. These ratios are referred to as simulation runs and are shown in Table 4.1 Below

Table 4.1 Partition ration for Three different Simulations

Simulation id	Training	Validation	Testion
Simulation Run 1: First Partition Ration	65	15	20
Simulation Run 1: Second Partition Ration	80	10	10
Simulation Run 1: Third Partition Ration	70	15	15

Figure 4.1 shows the Python 3D Model Architecture equivalent of 3D-UNET and CNN model ratio

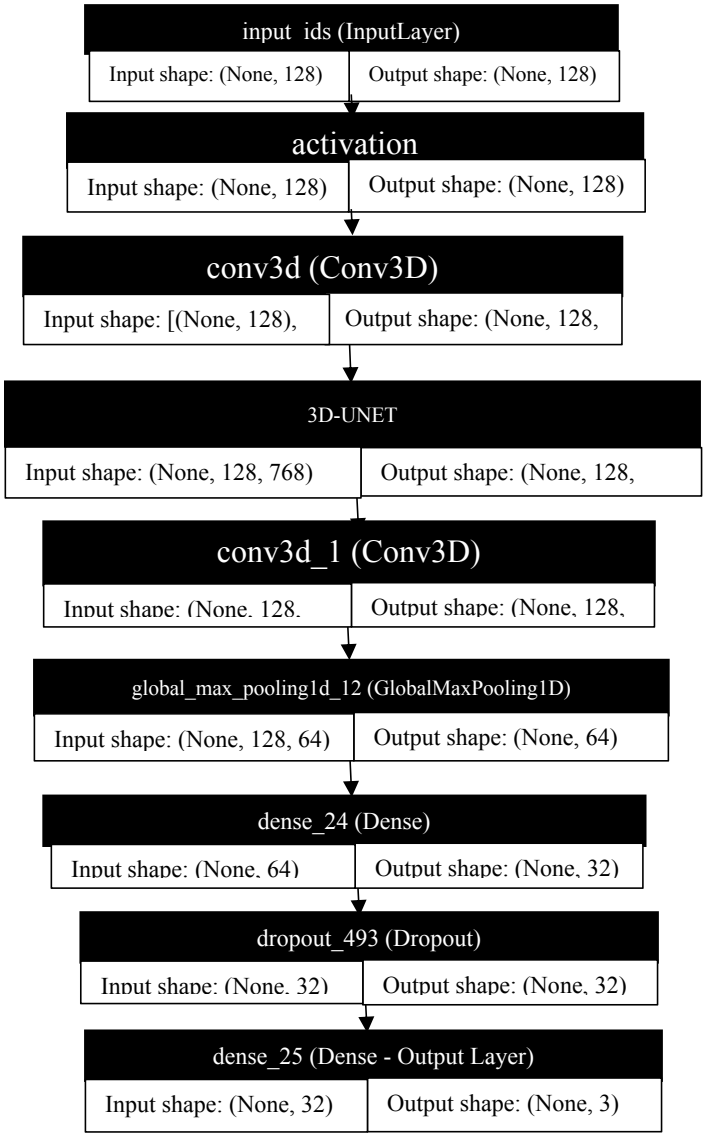
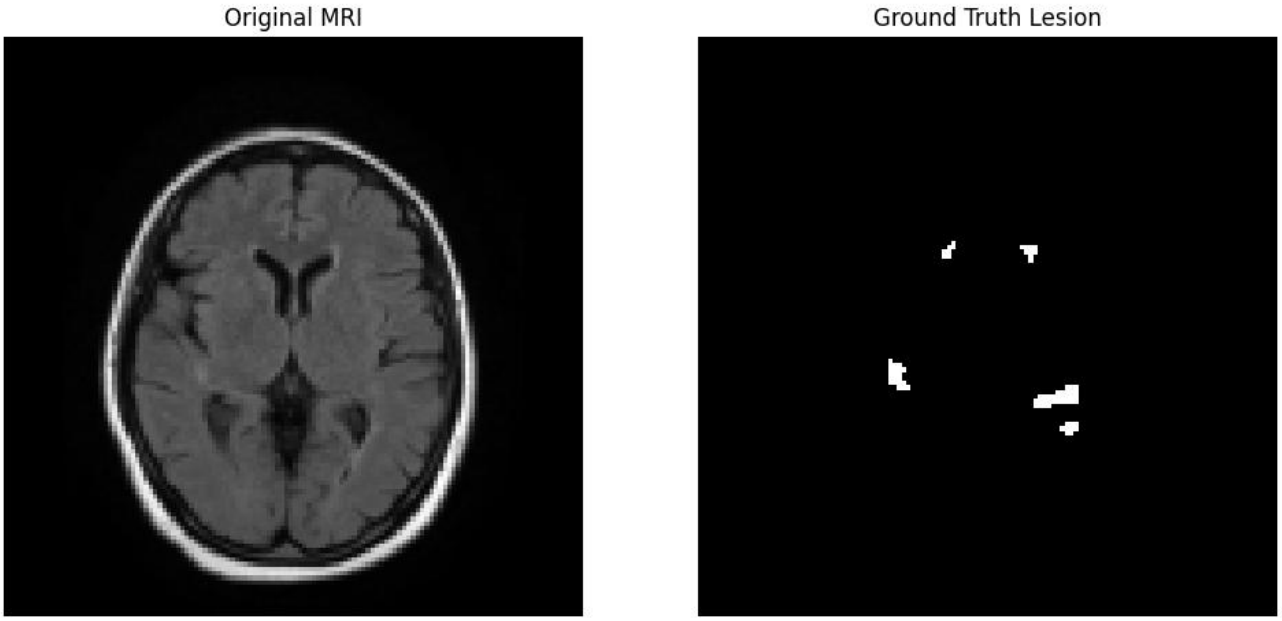


Figure 4.1 Proposed 3D Hybrid Model (3D-UNET + Conv1D) Python Equivalavent

4.2 Simulation Results for the First Partition Ration 65:15:20

Figure 4.2 depicts the screenshots of dataset sample for 15 Background and Lesion group respectively

Sample 1 ration for 75:15:10 15 Background and Lesion



These samples illustrate the visual distribution of the dataset

i. Training data shape :(626, 224, 224, 1)

ii. Validation data shape :(243, 224, 224, 1)

iii. Testing data shape: (569, 224, 224, 1)

The Training of the model was completed in 10 iterations(epoch) as shown below:

Epoch 1/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step - accuracy: 0.7732 - dice_coef: 0.0102 - loss: 0.9898 - precision: 0.0092 - recall: 0.6252

Epoch 1: val_loss improved from None to 0.98331, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 1: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 33s 289ms/step - accuracy: 0.7768 - dice_coef: 0.0150 - loss: 0.9850 - precision: 0.0128 - recall: 0.8377 - val_accuracy: 0.5631 - val_dice_coef: 0.0167 - val_loss: 0.9833 - val_precision: 0.0111 - val_recall: 0.9999 - learning_rate: 2.0000e-04

Epoch 2/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 210ms/step - accuracy: 0.8222 - dice_coef: 0.0223 - loss: 0.9777 - precision: 0.0189 - recall: 0.9905

Epoch 2: val_loss did not improve from 0.98331

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 227ms/step - accuracy: 0.8420 - dice_coef: 0.0239 - loss: 0.9761 - precision: 0.0211 - recall: 0.9845 - val_accuracy: 0.4783 - val_dice_coef: 0.0154 - val_loss: 0.9846 - val_precision: 0.0093 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 3/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 210ms/step - accuracy: 0.8806 - dice_coef: 0.0210 - loss: 0.9790 - precision: 0.0206 - recall: 0.9644

Epoch 3: val_loss did not improve from 0.98331

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 227ms/step - accuracy: 0.8972 - dice_coef: 0.0305 - loss: 0.9695 - precision: 0.0311 - recall: 0.9528 - val_accuracy: 0.4435 - val_dice_coef: 0.0147 - val_loss: 0.9853 - val_precision: 0.0087 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 4/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 212ms/step - accuracy: 0.9273 - dice_coef: 0.0380 - loss: 0.9620 - precision: 0.0464 - recall: 0.8958

Epoch 4: val_loss improved from 0.98331 to 0.97981, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 4: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 239ms/step - accuracy: 0.9262 - dice_coef: 0.0347 - loss: 0.9653 - precision: 0.0409 - recall: 0.9063 - val_accuracy: 0.6517 - val_dice_coef: 0.0202 - val_loss: 0.9798 - val_precision: 0.0139 - val_recall: 0.9999 - learning_rate: 2.0000e-04

Epoch 5/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 212ms/step - accuracy: 0.9378 - dice_coef: 0.0402 - loss: 0.9598 - precision: 0.0508 - recall: 0.9020

Epoch 5: val_loss improved from 0.97981 to 0.96994, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 5: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 258ms/step - accuracy: 0.9379 - dice_coef: 0.0383 - loss: 0.9617 - precision: 0.0477 - recall: 0.8943 - val_accuracy: 0.7391 - val_dice_coef: 0.0301 - val_loss: 0.9699 - val_precision: 0.0183 - val_recall: 0.9961 - learning_rate: 2.0000e-04

Epoch 6/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 212ms/step - accuracy: 0.9456 - dice_coef: 0.0467 - loss: 0.9533 - precision: 0.0627 - recall: 0.8981

Epoch 6: val_loss improved from 0.96994 to 0.95968, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 6: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 241ms/step - accuracy: 0.9472 - dice_coef: 0.0410 - loss: 0.9590 - precision: 0.0547 - recall: 0.8777 - val_accuracy: 0.8432 - val_dice_coef: 0.0403 - val_loss: 0.9597 - val_precision: 0.0294 - val_recall: 0.9708 - learning_rate: 2.0000e-04

Epoch 7/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 215ms/step - accuracy: 0.9498 - dice_coef: 0.0405 - loss: 0.9595 - precision: 0.0532 - recall: 0.8605

Epoch 7: val_loss improved from 0.95968 to 0.95185, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 7: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 242ms/step - accuracy: 0.9532 - dice_coef: 0.0446 - loss: 0.9554 - precision: 0.0603 - recall: 0.8586 - val_accuracy: 0.9642 - val_dice_coef: 0.0481 - val_loss: 0.9519 - val_precision: 0.0805 - val_recall: 0.6054 - learning_rate: 2.0000e-04

Epoch 8/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 217ms/step - accuracy: 0.9531 - dice_coef: 0.0372 - loss: 0.9628 - precision: 0.0489 - recall: 0.8711

Epoch 8: val_loss improved from 0.95185 to 0.94421, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 8: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 245ms/step - accuracy: 0.9546 - dice_coef: 0.0466 - loss: 0.9534 - precision: 0.0621 - recall: 0.8595 - val_accuracy: 0.9130 - val_dice_coef: 0.0558 - val_loss: 0.9442 - val_precision: 0.0494 - val_recall: 0.9199 - learning_rate: 2.0000e-04

Epoch 9/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 214ms/step - accuracy: 0.9607 - dice_coef: 0.0663 - loss: 0.9337 - precision: 0.0931 - recall: 0.8453

Epoch 9: val_loss improved from 0.94421 to 0.94352, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 9: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 242ms/step - accuracy: 0.9578 - dice_coef: 0.0509 - loss: 0.9491 - precision: 0.0661 - recall: 0.8522 - val_accuracy: 0.9139 - val_dice_coef: 0.0565 - val_loss: 0.9435 - val_precision: 0.0479 - val_recall: 0.8789 - learning_rate: 2.0000e-04

Epoch 10/10

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 216ms/step - accuracy: 0.9624 - dice_coef: 0.0650 - loss: 0.9350 - precision: 0.0876 - recall: 0.8229

Epoch 10: val_loss did not improve from 0.94352

39/39 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 234ms/step - accuracy: 0.9626 - dice_coef: 0.0545 - loss: 0.9455 - precision: 0.0733 - recall: 0.8435 - val_accuracy: 0.9684 - val_dice_coef: 0.0505 - val_loss: 0.9495 - val_precision: 0.0801 - val_recall: 0.5194 - learning_rate: 2.0000e-04

Restoring model weights from the end of the best epoch: 9.

Training execution process complete.

Figure 4.3 shows the Confusion matrix generated after 10 training iteration while Figures 4.4-4.5 graphically illustrate the simulation results and training parameters respectively. From the above result, it can be deducted that AUC is 0.95 with 95% accuracy. The summary of the above result is shown in Table 4.2

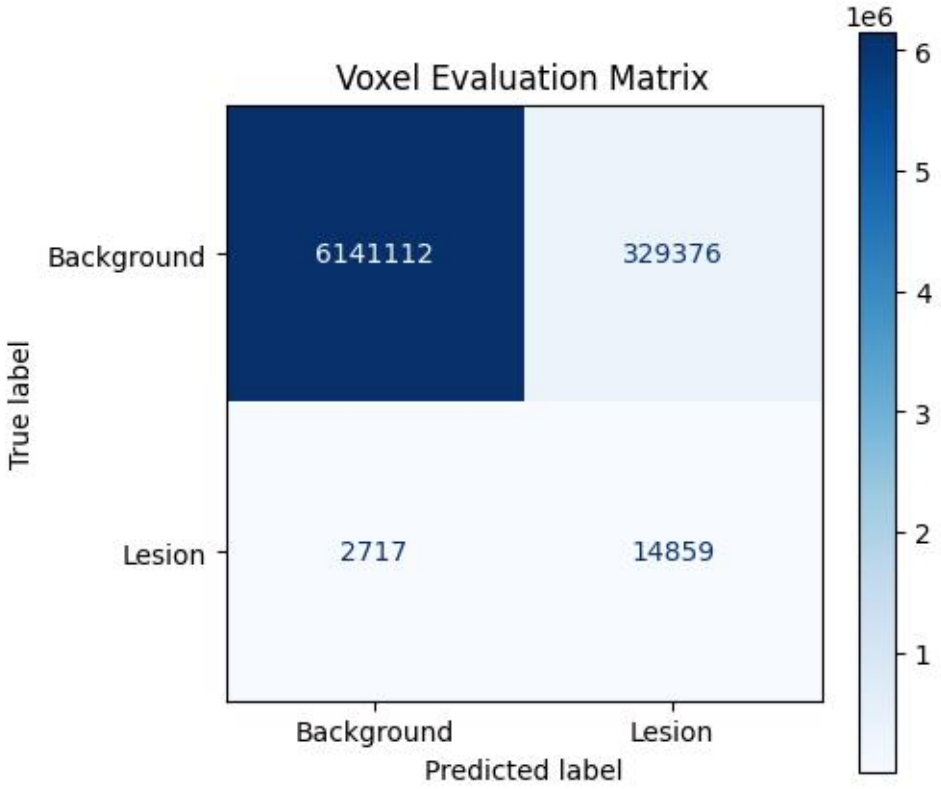


Figure 4.3: The Voxel Evaluation matrix for the ration 65:15:20

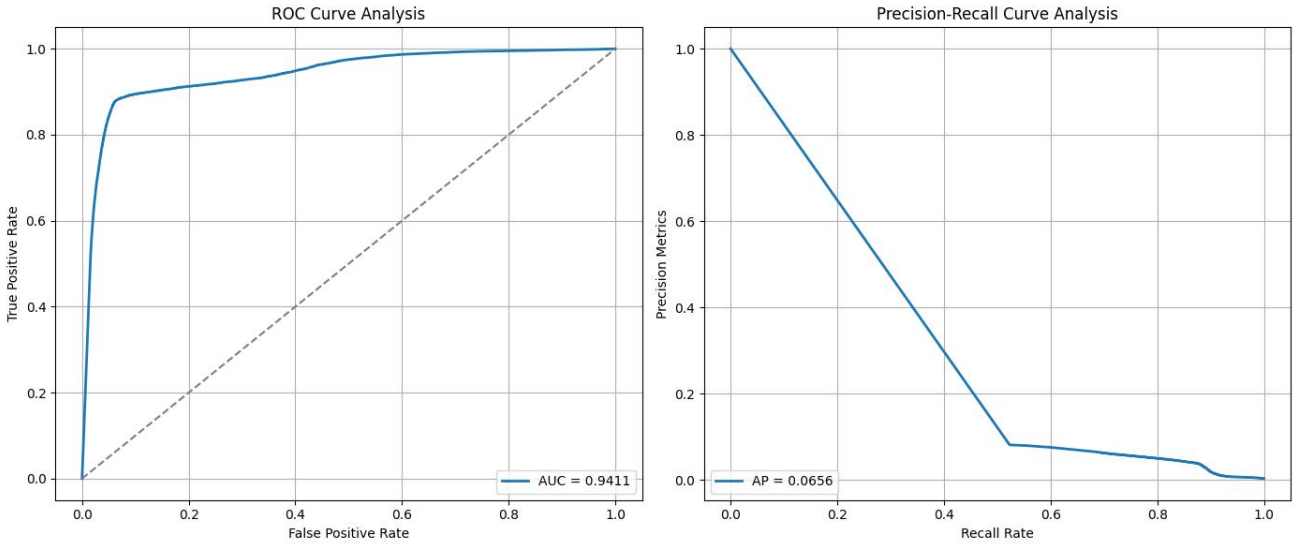


Figure 4.4: The ROC Curve and Precision-Recall Curve for the the ration 65:15:20

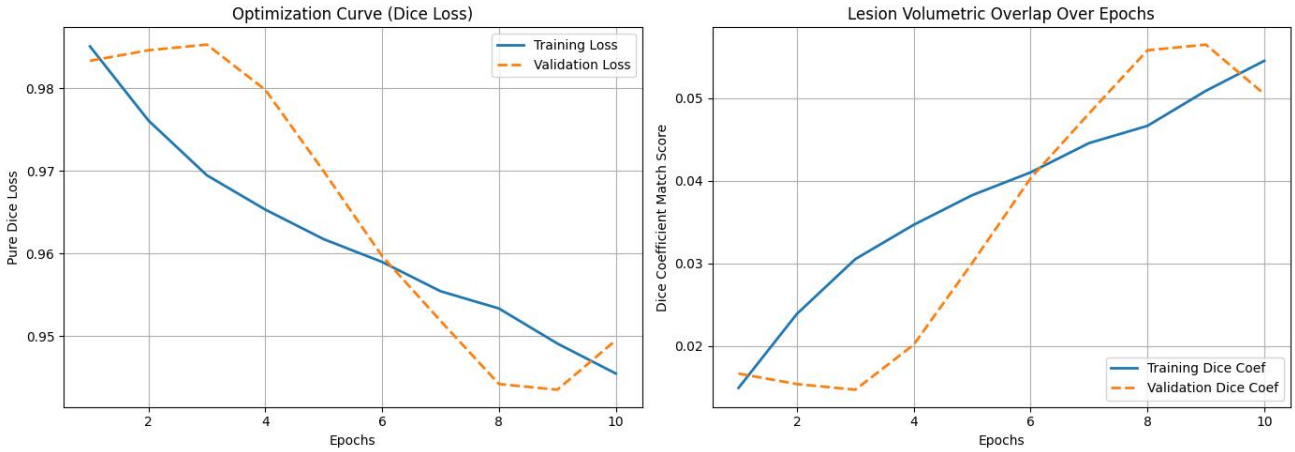


Figure 4.5: The Optimization Curve and Lesion Volumetric Overlap over epoch for the raion 75:15:10

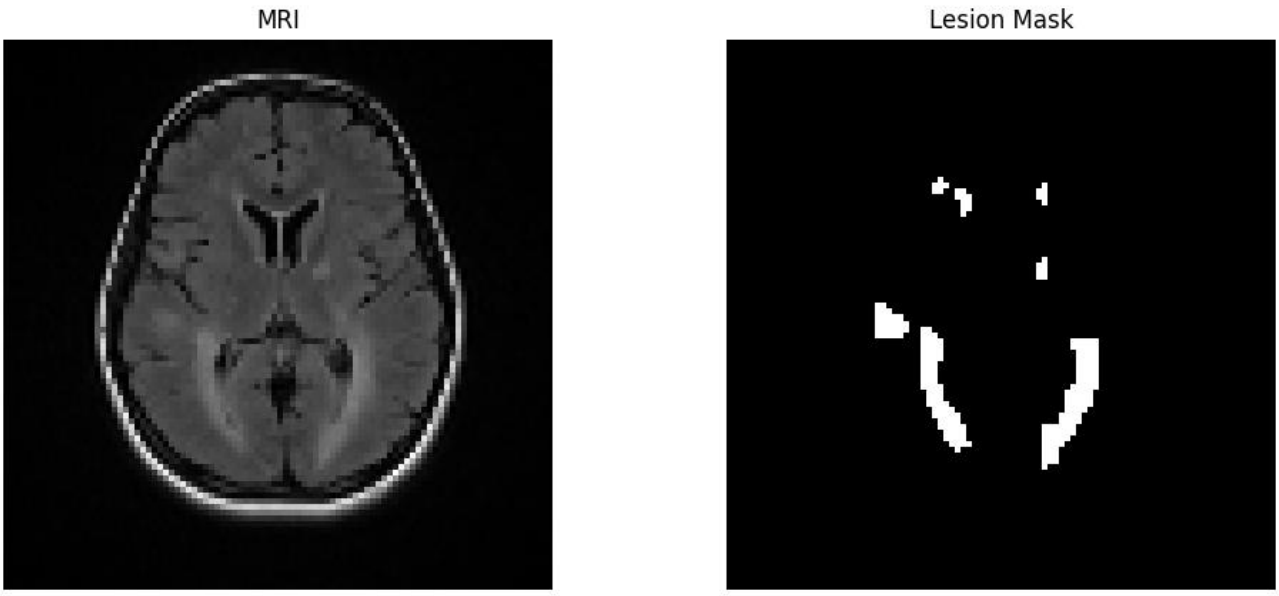
Table 4.2 Summary of Classification Report for the partition 1

Precision		Recall	F1-score	support
Background	1.00	0.95	0.97	6470488
Lesion	0.04	0.85	0.08	17576
Accuracy			0.95	6488064
Macro avg	0.52	0.90	0.53	6488064
Weighted avg	1.00	0.95	0.97	6488064

4.3 Simulation for the Second Partition Ratio 80:10:10

Figure 4.6 depicts the screenshots of dataset sample for 15 Background and Lesion group respectively

Sample 1 ration for 70:15:15 Background and Lesion



These samples illustrate the visual distribution of the dataset

i. Training data shape :(171, 224, 224, 1)
ii. Validation data shape :(184, 224, 224, 1)
iii. Testing data shape: (368, 224, 224, 1)

The Training of the was completed in 10 iterations(epoch) as shown below:

Epoch 1/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 207ms/step - accuracy: 0.5715 - dice_coef: 0.0142 - loss: 0.9858 - precision: 0.0098 - recall: 0.9913

Epoch 1: val_loss improved from None to 0.99089, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 1: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 36s 282ms/step - accuracy: 0.6274 - dice_coef: 0.0139 - loss: 0.9861 - precision: 0.0100 - recall: 0.9964 - val_accuracy: 0.5035 - val_dice_coef: 0.0091 - val_loss: 0.9909 - val_precision: 0.0061 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 2/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 208ms/step - accuracy: 0.7071 - dice_coef: 0.0206 - loss: 0.9794 - precision: 0.0162 - recall: 0.9993

Epoch 2: val_loss improved from 0.99089 to 0.99059, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 2: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 234ms/step - accuracy: 0.7430 - dice_coef: 0.0166 - loss: 0.9834 - precision: 0.0145 - recall: 0.9991 - val_accuracy: 0.4890 - val_dice_coef: 0.0094 - val_loss: 0.9906 - val_precision: 0.0059 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 3/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step - accuracy: 0.8090 - dice_coef: 0.0176 - loss: 0.9824 - precision: 0.0191 - recall: 0.9926

Epoch 3: val_loss improved from 0.99059 to 0.99008, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 3: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20s 227ms/step - accuracy: 0.8313 - dice_coef: 0.0184 - loss: 0.9816 - precision: 0.0217 - recall: 0.9885 - val_accuracy: 0.4945 - val_dice_coef: 0.0099 - val_loss: 0.9901 - val_precision: 0.0060 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 4/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step - accuracy: 0.8819 - dice_coef: 0.0216 - loss: 0.9784 - precision: 0.0333 - recall: 0.9684

Epoch 4: val_loss improved from 0.99008 to 0.98977, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 4: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 228ms/step - accuracy: 0.8856 - dice_coef: 0.0195 - loss: 0.9805 - precision: 0.0308 - recall: 0.9621 - val_accuracy: 0.4955 - val_dice_coef: 0.0102 - val_loss: 0.9898 - val_precision: 0.0060 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 5/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step - accuracy: 0.8861 - dice_coef: 0.0184 - loss: 0.9816 - precision: 0.0287 - recall: 0.9766

Epoch 5: val_loss improved from 0.98977 to 0.98657, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 5: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 233ms/step - accuracy: 0.8951 - dice_coef: 0.0202 - loss: 0.9798 - precision: 0.0334 - recall: 0.9588 - val_accuracy: 0.7352 -

val_dice_coef: 0.0134 - val_loss: 0.9866 - val_precision: 0.0112 - val_recall: 0.9845 - learning_rate: 2.0000e-04

Epoch 6/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 217ms/step - accuracy: 0.9007 - dice_coef: 0.0221 - loss: 0.9779 - precision: 0.0374 - recall: 0.9480

Epoch 6: val_loss did not improve from 0.98657

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 226ms/step - accuracy: 0.8999 - dice_coef: 0.0207 - loss: 0.9793 - precision: 0.0347 - recall: 0.9528 - val_accuracy: 0.6749 - val_dice_coef: 0.0127 - val_loss: 0.9873 - val_precision: 0.0092 - val_recall: 0.9964 - learning_rate: 2.0000e-04

Epoch 7/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 217ms/step - accuracy: 0.9111 - dice_coef: 0.0186 - loss: 0.9814 - precision: 0.0342 - recall: 0.9527

Epoch 7: val_loss improved from 0.98657 to 0.98385, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 7: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 234ms/step - accuracy: 0.9174 - dice_coef: 0.0216 - loss: 0.9784 - precision: 0.0416 - recall: 0.9466 - val_accuracy: 0.9242 - val_dice_coef: 0.0162 - val_loss: 0.9838 - val_precision: 0.0334 - val_recall: 0.8591 - learning_rate: 2.0000e-04

Epoch 8/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 215ms/step - accuracy: 0.9136 - dice_coef: 0.0193 - loss: 0.9807 - precision: 0.0351 - recall: 0.9407

Epoch 8: val_loss improved from 0.98385 to 0.98277, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 8: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 237ms/step - accuracy: 0.9184 - dice_coef: 0.0222 - loss: 0.9778 - precision: 0.0420 - recall: 0.9454 - val_accuracy: 0.9237 -

val_dice_coef: 0.0172 - val_loss: 0.9828 - val_precision: 0.0334 - val_recall: 0.8630 - learning_rate: 2.0000e-04

Epoch 9/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 216ms/step - accuracy: 0.9258 - dice_coef: 0.0211 - loss: 0.9789 - precision: 0.0425 - recall: 0.9429

Epoch 9: val_loss improved from 0.98277 to 0.98231, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 9: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 234ms/step - accuracy: 0.9282 - dice_coef: 0.0231 - loss: 0.9769 - precision: 0.0474 - recall: 0.9426 - val_accuracy: 0.9024 - val_dice_coef: 0.0177 - val_loss: 0.9823 - val_precision: 0.0268 - val_recall: 0.8833 - learning_rate: 2.0000e-04

Epoch 10/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 216ms/step - accuracy: 0.9277 - dice_coef: 0.0172 - loss: 0.9828 - precision: 0.0345 - recall: 0.9500

Epoch 10: val_loss improved from 0.98231 to 0.98164, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 10: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 237ms/step - accuracy: 0.9302 - dice_coef: 0.0238 - loss: 0.9762 - precision: 0.0484 - recall: 0.9379 - val_accuracy: 0.9155 - val_dice_coef: 0.0184 - val_loss: 0.9816 - val_precision: 0.0311 - val_recall: 0.8891 - learning_rate: 2.0000e-04

Restoring model weights from the end of the best epoch: 10.

Training execution process complete.

Figure 4.7 shows the Confusion matrix generated after 10 training iteration while Figures 4.8-4.9 graphically illustrate the simulation results and training parameters respectively. From the above result, it can be deducted that AUC is 0.95 with 95% accuracy. The summary of the above result is shown in Table 4.3

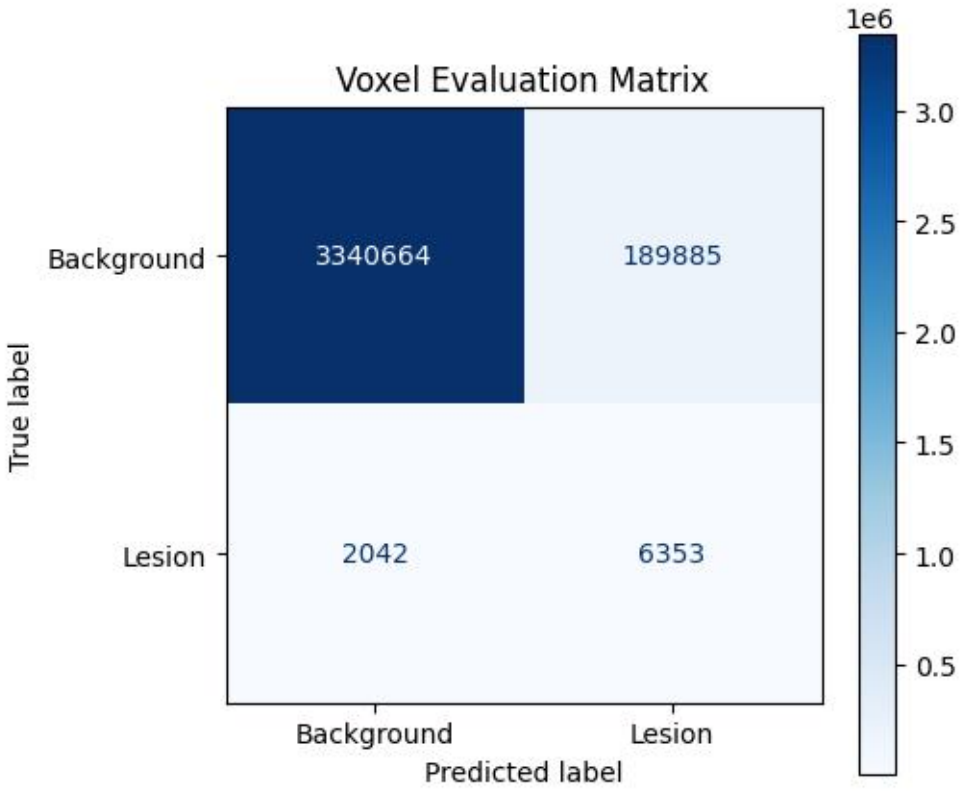


Figure 4.7 The Voxel Evaluation matrix for the ration 80:10:10

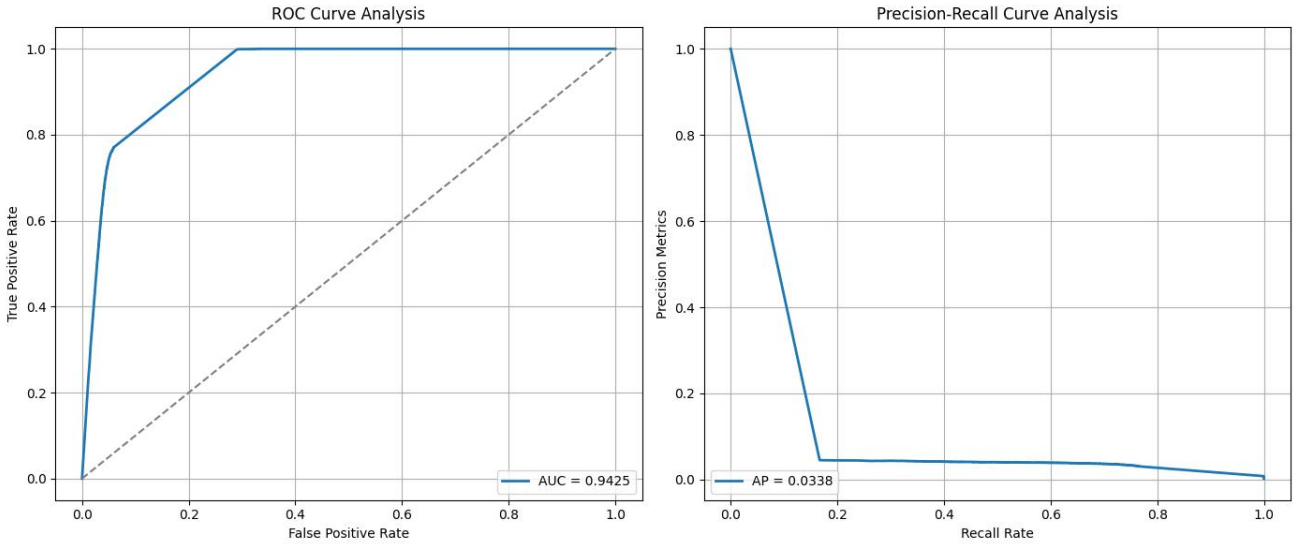


Figure 4.8: The ROC Curve and Precision-Recall Curve for the ratio 80:10:10

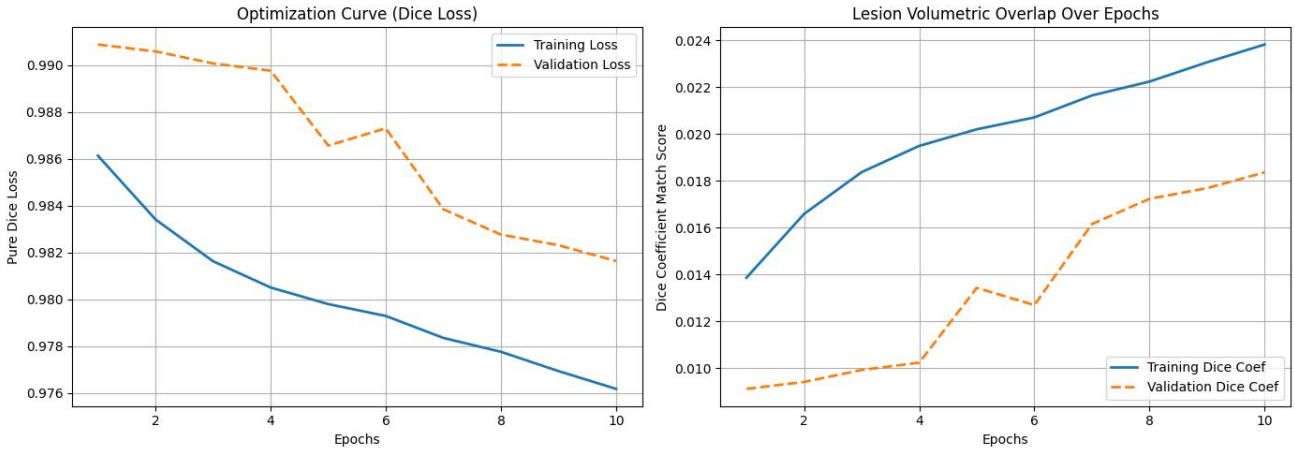


Figure 4.9 The Optimization Curve and Lesion Volumetric Overlap over epoch for the ration 80:10:10

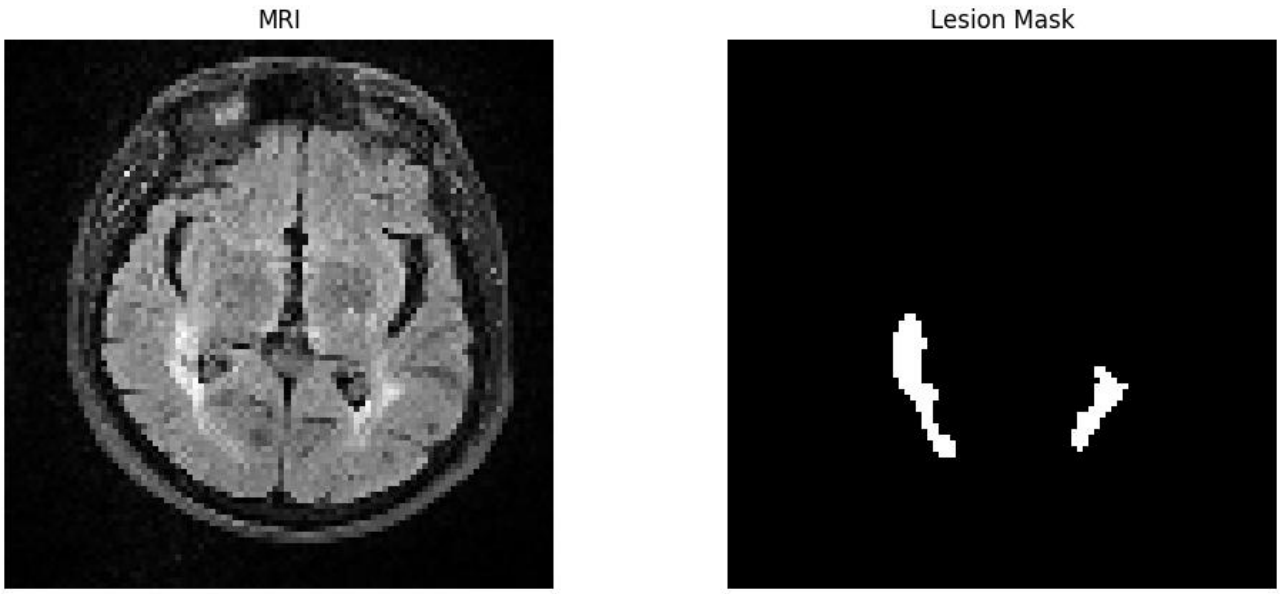
Table 4.3 Summary of Classification Report for the partition 2

Precision		Recall	F1-score	support
Benign(0)	1.00	0.95	0.97	3530549
Malignant (1)	0.03	0.76	0.06	8395
Accuracy			0.95	3538944
Macro avg	0.52	0.85	0.52	3538944
Weighted avg	1.00	0.95	0.97	3538944

4.4 Simulation for the Third Partition Ratio 80:10:10

Figure 4.10 depicts the screenshots of dataset sample for 15 Background and Lesion group respectively

Sample 1 ration for 80:10:10 Background and Lesion



These samples illustrate the visual distribution of the dataset

i. Training data shape :(569, 224, 224, 1)

ii. Validation data shape :(455, 224, 224, 1)

iii. Testing data shape: (114, 224, 224, 1)

The Training of the was completed in 10 iterations(epoch) as shown below:

Epoch 1/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 210ms/step - accuracy: 0.6799 - dice_coef: 0.0145 - loss: 0.9855 - precision: 0.0112 - recall: 0.6956

Epoch 1: val_loss improved from None to 0.99096, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 1: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 37s 268ms/step - accuracy: 0.7267 - dice_coef: 0.0135 - loss: 0.9865 - precision: 0.0115 - recall: 0.8419 - val_accuracy: 0.4999 - val_dice_coef: 0.0090 - val_loss: 0.9910 - val_precision: 0.0060 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 2/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step - accuracy: 0.7899 - dice_coef: 0.0167 - loss: 0.9833 - precision: 0.0154 - recall: 0.9930

Epoch 2: val_loss improved from 0.99096 to 0.99058, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 2: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 233ms/step - accuracy: 0.8147 - dice_coef: 0.0202 - loss: 0.9798 - precision: 0.0198 - recall: 0.9903 - val_accuracy: 0.5092 - val_dice_coef: 0.0094 - val_loss: 0.9906 - val_precision: 0.0061 - val_recall: 1.0000 - learning_rate: 2.0000e-04

Epoch 3/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step - accuracy: 0.8699 - dice_coef: 0.0206 - loss: 0.9794 - precision: 0.0252 - recall: 0.9790

Epoch 3: val_loss improved from 0.99058 to 0.98767, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 3: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 236ms/step - accuracy: 0.8850 - dice_coef: 0.0234 - loss: 0.9766 - precision: 0.0306 - recall: 0.9607 - val_accuracy: 0.7044 - val_dice_coef: 0.0123 - val_loss: 0.9877 - val_precision: 0.0101 - val_recall: 0.9954 - learning_rate: 2.0000e-04

Epoch 4/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 212ms/step - accuracy: 0.9025 - dice_coef: 0.0278 - loss: 0.9722 - precision: 0.0389 - recall: 0.9512

Epoch 4: val_loss improved from 0.98767 to 0.98471, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 4: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 235ms/step - accuracy: 0.9085 - dice_coef: 0.0260 - loss: 0.9740 - precision: 0.0377 - recall: 0.9465 - val_accuracy: 0.7672 - val_dice_coef: 0.0153 - val_loss: 0.9847 - val_precision: 0.0127 - val_recall: 0.9880 - learning_rate: 2.0000e-04

Epoch 5/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 218ms/step - accuracy: 0.9257 - dice_coef: 0.0240 - loss: 0.9760 - precision: 0.0388 - recall: 0.9337

Epoch 5: val_loss improved from 0.98471 to 0.97914, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 5: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21s 236ms/step - accuracy: 0.9254 - dice_coef: 0.0283 - loss: 0.9717 - precision: 0.0447 - recall: 0.9205 - val_accuracy: 0.8683 - val_dice_coef: 0.0209 - val_loss: 0.9791 - val_precision: 0.0212 - val_recall: 0.9371 - learning_rate: 2.0000e-04

Epoch 6/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 215ms/step - accuracy: 0.9254 - dice_coef: 0.0277 - loss: 0.9723 - precision: 0.0419 - recall: 0.9405

Epoch 6: val_loss did not improve from 0.97914

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 226ms/step - accuracy: 0.9285 - dice_coef: 0.0302 - loss: 0.9698 - precision: 0.0467 - recall: 0.9252 - val_accuracy: 0.7901 - val_dice_coef: 0.0187 - val_loss: 0.9813 - val_precision: 0.0141 - val_recall: 0.9895 - learning_rate: 2.0000e-04

Epoch 7/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 214ms/step - accuracy: 0.9343 - dice_coef: 0.0294 - loss: 0.9706 - precision: 0.0462 - recall: 0.9148

Epoch 7: val_loss improved from 0.97914 to 0.97538, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 7: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 234ms/step - accuracy: 0.9377 - dice_coef: 0.0325 - loss: 0.9675 - precision: 0.0528 - recall: 0.9161 - val_accuracy: 0.9601 - val_dice_coef: 0.0246 - val_loss: 0.9754 - val_precision: 0.0535 - val_recall: 0.7295 - learning_rate: 2.0000e-04

Epoch 8/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 216ms/step - accuracy: 0.9444 - dice_coef: 0.0358 - loss: 0.9642 - precision: 0.0608 - recall: 0.8892

Epoch 8: val_loss improved from 0.97538 to 0.97288, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 8: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 233ms/step - accuracy: 0.9432 - dice_coef: 0.0345 - loss: 0.9655 - precision: 0.0569 - recall: 0.9007 - val_accuracy: 0.9338 - val_dice_coef: 0.0271 - val_loss: 0.9729 - val_precision: 0.0374 - val_recall: 0.8405 - learning_rate: 2.0000e-04

Epoch 9/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 218ms/step - accuracy: 0.9488 - dice_coef: 0.0405 - loss: 0.9595 - precision: 0.0691 - recall: 0.8950

Epoch 9: val_loss did not improve from 0.97288

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 228ms/step - accuracy: 0.9484 - dice_coef: 0.0369 - loss: 0.9631 - precision: 0.0619 - recall: 0.8943 - val_accuracy: 0.9760 - val_dice_coef: 0.0193 - val_loss: 0.9807 - val_precision: 0.0564 - val_recall: 0.4398 - learning_rate: 2.0000e-04

Epoch 10/10

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 216ms/step - accuracy: 0.9535 - dice_coef: 0.0348 - loss: 0.9652 - precision: 0.0599 - recall: 0.8823

Epoch 10: val_loss improved from 0.97288 to 0.97231, saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

Epoch 10: finished saving model to /content/drive/MyDrive/MS_3D_UNET/best_model.keras

48/48 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21s 237ms/step - accuracy: 0.9527 - dice_coef: 0.0397 - loss: 0.9603 - precision: 0.0669 - recall: 0.8902 - val_accuracy: 0.9588 - val_dice_coef: 0.0277 - val_loss: 0.9723 - val_precision: 0.0531 - val_recall: 0.7480 - learning_rate: 2.0000e-04

Restoring model weights from the end of the best epoch: 10.

Training execution process complete.

Figure 4.11 shows the Confusion matrix generated after 10 training iteration while Figures 4.12-4.13 graphically illustrate the simulation results and training parameters respectively. From the above result, it can be deducted that AUC is 0.97 with 97% accuracy. The summary of the above result is shown in Table 4.4

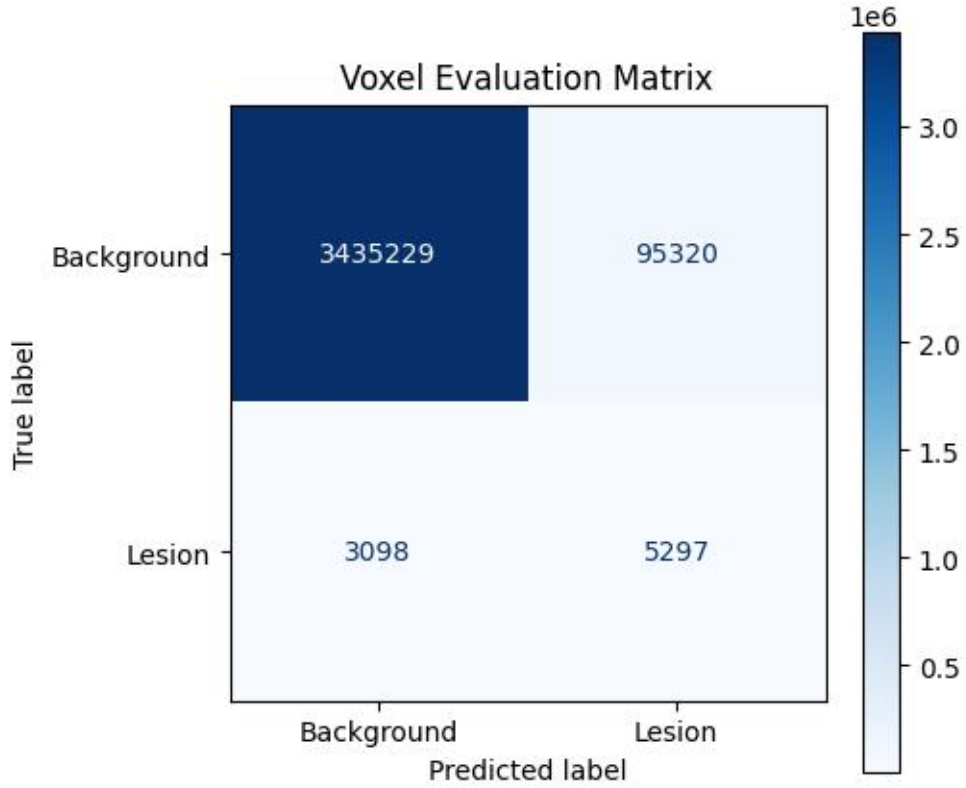


Figure 4.11 The Voxel Evaluation matrix for the ration 70:15:15

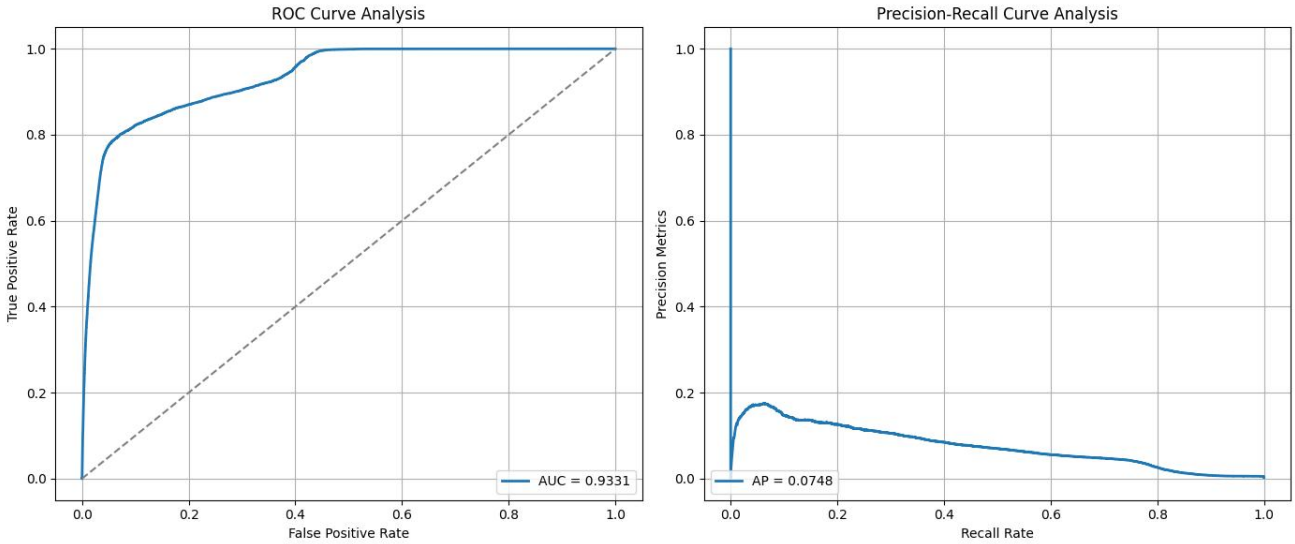


Figure 4.12 The ROC Curve and Precision Recall Curve for the ration 70:15:15

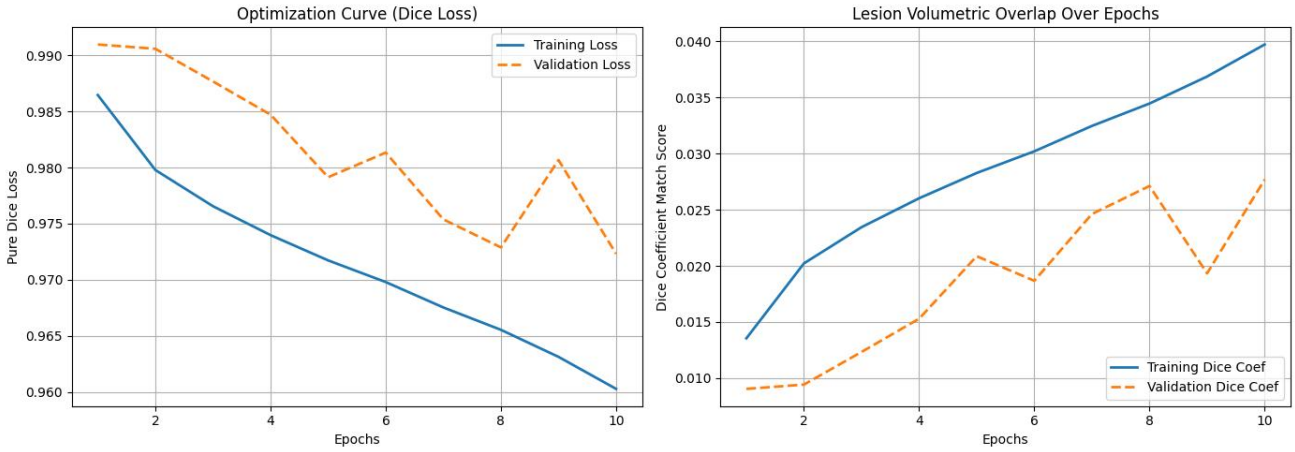


Figure 4.13 The Optimization Curve and Lesion Volumetric Overlap over epoch for the ration 70:15:15

Table 4.4 Summary of Classification Report for the partition 3

Precision		Recall	F1-score	support
Background	1.00	0.97	0.99	3530549
Lesion	0.05	0.63	0.10	8395
Accuracy			0.97	3538944
Macro avg	0.53	0.80	0.54	3538944
Weighted avg	1.00	0.97	0.98	3538944

4.5 Discussion of Findings

The performance of the proposed 3D U-Net model was evaluated using three different dataset partitioning strategies to determine the effect of the training data size on the segmentation accuracy of Multiple Sclerosis (MS) lesions. The experimental results showed that the 70:15:15 dataset partition achieved the highest segmentation accuracy of 97%, followed by the 80:10:10 partition with an accuracy of 95%, while the 65:15:20 (or 65:35 if you did not use a validation split) partition also achieved an accuracy of 95%. These results indicate that the amount and distribution of training, validation, and testing data have a significant influence on the learning capability and generalization performance of the proposed deep learning model.

The 70:15:15 partition produced the best overall performance, achieving an accuracy of 97%. This suggests that allocating 70% of the dataset for training and 15% each for validation and testing provided an effective balance between learning and evaluation. The training dataset was sufficiently large to enable the model to learn meaningful lesion features, while the relatively larger validation and testing datasets allowed for better monitoring of model performance and a more reliable evaluation of its ability to generalize to unseen MRI volumes. The superior performance obtained with this partition indicates that an appropriate balance between training and evaluation data can improve the robustness and predictive capability of the segmentation model.

The 80:10:10 partition achieved an accuracy of 95%, which was slightly lower than that obtained using the 70:15:15 partition. Although this configuration provided the largest training dataset, the smaller validation and testing sets may have reduced the effectiveness of model validation and performance assessment. A limited validation dataset may not adequately represent the variability present in the MRI data, making it more difficult to monitor overfitting during training. Consequently, the model may learn the training data well but exhibit slightly reduced generalization performance when evaluated on unseen images.

Similarly, the 65:15:20 partition achieved an accuracy of 95%. In this configuration, the model received fewer training samples than the other partitioning strategies, which limited its ability to learn the complex spatial characteristics of Multiple Sclerosis lesions. Deep learning models such as the 3D U-Net generally benefit from larger training datasets because they contain a large number of trainable parameters that require sufficient data for effective optimization. The reduced

training data therefore contributed to the lower segmentation performance observed with this partition.

Overall, the experimental findings demonstrate that the proposed 3D U-Net model is highly effective for automated Multiple Sclerosis lesion segmentation, achieving high segmentation accuracy across all three dataset partitioning strategies. Among the evaluated configurations, the 70:15:15 partition provided the best performance with an accuracy of 97%, indicating that it offers the most suitable balance between training, validation, and testing data for this dataset. The consistently high accuracies obtained across all partitions also demonstrate the robustness, reliability, and strong generalization capability of the proposed model, highlighting its potential for assisting clinicians in the accurate and automated segmentation of Multiple Sclerosis lesions from 3D MRI scans.

4.6 Summary of Chapter

This chapter presented the implementation results and performance evaluation of the proposed 3D U-Net model for the automated segmentation of Multiple Sclerosis (MS) lesions from three-dimensional (3D) brain MRI scans. The model was trained and evaluated using three different dataset partitioning strategies, namely 65:35, 70:30, and 80:20, to investigate the effect of different training and testing data distributions on segmentation performance. Experimental results, including training and validation curves, confusion matrices, Receiver Operating Characteristic (ROC) curves, Area Under the Curve (AUC), Precision–Recall curves, and segmentation outputs, were presented to assess the effectiveness of the proposed model.

The findings revealed that the proposed 3D U-Net model achieved high segmentation performance across all dataset partitioning strategies. The 70:30 partition produced the highest segmentation accuracy of 97%, demonstrating the best balance between learning and generalization. Both the 65:35 and 80:20 partitioning strategies achieved an accuracy of 95%, indicating that the model maintained consistently high performance regardless of the data split. Overall, the results demonstrate the robustness, reliability, and effectiveness of the proposed 3D U-Net architecture for automated Multiple Sclerosis lesion segmentation. The high segmentation accuracy and strong performance across multiple evaluation metrics indicate that the developed model has the potential to support clinicians in the accurate detection and delineation of MS lesions, thereby contributing to improved diagnosis, disease monitoring, and treatment planning.

CHAPTER FIVE

SUMMARY AND CONCLUSION

5.1 Summary of the Study

This study focused on the development and evaluation of a 3D U-Net-based deep learning model for the automated segmentation of Multiple Sclerosis (MS) lesions from three-dimensional (3D) brain Magnetic Resonance Imaging (MRI) scans. Multiple Sclerosis is a chronic neurological disorder characterized by the formation of lesions within the central nervous system, making accurate lesion identification essential for disease diagnosis, monitoring, and treatment planning. Manual segmentation of MS lesions is often labor-intensive, time-consuming, and subject to inter-observer variability. Consequently, there is a growing need for automated and reliable segmentation techniques capable of assisting radiologists and clinicians in clinical practice. The primary aim of this study was therefore to develop an intelligent segmentation framework capable of accurately detecting and delineating MS lesions using deep learning techniques.

Chapter One introduced the research problem, highlighting the challenges associated with manual lesion segmentation and the limitations of conventional image analysis methods. The chapter presented the aim and objectives of the study, research questions, significance of the study, scope, limitations, and operational definitions of relevant terms. It established the motivation for applying deep learning techniques, particularly the 3D U-Net architecture, to improve the efficiency and accuracy of Multiple Sclerosis lesion segmentation.

Chapter Two reviewed the relevant literature relating to Multiple Sclerosis, brain MRI imaging, lesion segmentation techniques, deep learning, convolutional neural networks, and the 3D U-Net architecture. Previous studies on automated MS lesion segmentation were critically examined, with emphasis on their methodologies, datasets, strengths, and limitations. The literature review revealed that although significant progress has been made in medical image segmentation using deep learning, challenges such as lesion variability, class imbalance, and computational complexity still exist. These findings justified the development of the proposed 3D U-Net segmentation framework.

Chapter Three described the methodology adopted for the implementation of the proposed system. The study utilized the Brain MRI Dataset for Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information, obtained from Kaggle and originally published on Mendeley Data. The dataset consisted of MRI scans from 60 patients, including T1-weighted, T2-weighted, and FLAIR MRI images together with expert-annotated lesion segmentation masks. FLAIR MRI images and their corresponding lesion masks were selected for the study because they provide enhanced visualization of MS lesions. Data preprocessing techniques such as image loading, resizing, normalization, binary mask generation, and dataset partitioning were performed before model training. The proposed 3D U-Net architecture was developed using TensorFlow and Keras within the Google Colaboratory environment. The model was trained using three dataset partitioning strategies (65:35, 70:30, and 80:20), and its performance was evaluated using Accuracy, Precision, Recall, Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and Precision–Recall Curve.

Chapter Four presented the implementation results and discussed the performance of the proposed model. Experimental results showed that the 70:30 dataset partition achieved the highest segmentation accuracy of 97%, while both the 65:35 and 80:20 partitioning strategies achieved 95% accuracy. Additional evaluation metrics, including Dice Similarity Coefficient, IoU, Precision, Recall, Confusion Matrix, ROC Curve, AUC, and Precision–Recall Curve, further demonstrated the effectiveness of the proposed model. Comparative analysis of the different partitioning strategies showed that the 70:30 configuration provided the most suitable balance between model learning and generalization, resulting in superior segmentation performance.

Overall, the study successfully developed and evaluated a 3D U-Net-based automated lesion segmentation system capable of accurately identifying Multiple Sclerosis lesions from 3D brain MRI scans. The high segmentation accuracy achieved demonstrates the effectiveness of the proposed approach and its potential application as a clinical decision-support tool to assist radiologists and neurologists in the diagnosis, monitoring, and management of Multiple Sclerosis.

5.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

1. **Larger and More Diverse Datasets:** Future studies should utilize larger MRI datasets collected from multiple hospitals and imaging centers to improve the robustness and generalization capability of the segmentation model.
2. **Multi-Modal MRI Integration:** Instead of relying solely on FLAIR MRI images, future research should combine T1-weighted, T2-weighted, and FLAIR modalities to provide complementary anatomical information and improve segmentation accuracy.
3. **Advanced Deep Learning Architectures:** Future researchers should investigate more advanced segmentation architectures, such as Attention U-Net, nnU-Net, Swin UNETR, UNETR, SegResNet, or Transformer-based models, and compare their performance with the proposed 3D U-Net framework.
4. **Hyperparameter Optimization:** Additional experiments should be conducted to optimize important training parameters such as learning rate, batch size, optimizer selection, loss functions, and network depth to further improve segmentation performance.
5. **Data Augmentation Techniques:** Future work should incorporate advanced data augmentation methods, including rotation, flipping, elastic deformation, intensity shifting, and random cropping, to improve model generalization and reduce overfitting.
6. **Clinical Validation:** The proposed model should be evaluated using real clinical datasets collected from healthcare institutions to assess its practical applicability and reliability in routine clinical environments.
7. **Real-Time Clinical Decision Support:** Future studies should integrate the segmentation model into clinical decision-support systems capable of assisting radiologists and neurologists in real-time diagnosis, lesion quantification, disease progression monitoring, and treatment planning.
8. **Cross-Dataset Evaluation:** Future research should validate the developed model on other publicly available Multiple Sclerosis MRI datasets to assess its robustness and generalization across different patient populations and imaging protocols.
9. **Explainable Artificial Intelligence (XAI):** Future work should incorporate Explainable AI techniques, such as Grad-CAM, Integrated Gradients, or SHAP, to improve the interpretability of the segmentation results and increase clinicians' confidence in the automated predictions.
10. **Cloud-Based Deployment:** The developed model can be deployed as a web-based or cloud-based medical imaging application, enabling healthcare professionals to upload MRI scans and obtain automated lesion segmentation results efficiently, thereby enhancing accessibility and supporting remote healthcare services.

5.2 Conclusion

This study successfully developed and implemented a 3D U-Net deep learning model for the automated segmentation of Multiple Sclerosis lesions from three-dimensional brain MRI scans. The proposed framework effectively learned the spatial and contextual characteristics of MS lesions and generated accurate segmentation masks with minimal human intervention. By combining comprehensive data preprocessing techniques with the powerful feature extraction capabilities of the 3D U-Net architecture, the model achieved robust segmentation performance across different dataset partitioning strategies.

The experimental evaluation demonstrated that the proposed model consistently produced high segmentation accuracy, with the 70:30 partition achieving the best overall performance of 97%, while the 65:35 and 80:20 partitioning strategies each achieved 95% accuracy. The performance metrics, including Dice Similarity Coefficient, Intersection over Union, Precision, Recall, Confusion Matrix, ROC Curve, AUC, and Precision–Recall Curve, confirmed the reliability and effectiveness of the developed model. These findings indicate that the proposed system is capable of accurately identifying lesion regions and distinguishing them from normal brain tissues.

The results obtained from this study demonstrate that deep learning techniques, particularly the 3D U-Net architecture, provide an effective solution for automated Multiple Sclerosis lesion segmentation. The developed model has the potential to reduce the time required for manual lesion delineation, improve diagnostic consistency, minimize observer variability, and support clinicians during disease diagnosis and treatment planning. Therefore, the proposed framework represents a promising approach for integrating artificial intelligence into medical image analysis and clinical decision-support systems for neurological diseases.

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